



BANK OF CANADA
BANQUE DU CANADA

Working Paper/Document de travail
2014-54

International House Price Cycles, Monetary Policy and Risk Premiums

by Gregory H. Bauer

Bank of Canada Working Paper 2014-54

December 2014

International House Price Cycles, Monetary Policy and Risk Premiums

by

Gregory H. Bauer

Canadian Economic Analysis Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
gbauer@bankofcanada.ca

Bank of Canada working papers are theoretical or empirical works-in-progress on subjects in economics and finance. The views expressed in this paper are those of the author. No responsibility for them should be attributed to the Bank of Canada.

Acknowledgements

Much thanks to Monica Mow for excellent research assistance.

Abstract

Using a panel logit framework, the paper provides an estimate of the likelihood of a house price correction in 18 OECD countries. The analysis shows that a simple measure of the degree of house price overvaluation contains a lot of information about subsequent price reversals. Corrections are typically triggered by a sharp tightening in the monetary policy interest rate relative to a baseline level in each country. Two different assessments of the current and future baseline estimates of monetary policy interest rates are provided: a simple Taylor rule and one extracted from a term structure model. A case study based on the Canadian housing market is presented.

JEL classification: C2, E43, R21

Bank classification: Housing; Econometric and statistical methods

Résumé

À partir d'un modèle logit avec données de panel est fournie une estimation de la probabilité d'une correction des prix des logements dans 18 pays de l'OCDE. L'analyse montre qu'une mesure simple du degré de surévaluation des prix des logements contient une grande quantité d'informations sur les changements ultérieurs de prix. Les corrections de prix sont généralement provoquées par un relèvement marqué du taux directeur au regard de son niveau de référence dans chaque pays. L'étude fournit deux modes d'évaluation différents des estimations de référence du niveau actuel et futur des taux directeurs : d'un côté, une règle de Taylor simple, et de l'autre, une règle fondée sur un modèle à structure par terme. Une étude de cas du marché canadien du logement est présentée.

Classification JEL : C2, E43, R21

Classification de la Banque : Logement; Méthodes économétriques et statistiques

1 Introduction

The recent financial crisis has highlighted the importance of housing markets as both a source and a transmission mechanism of financial instability. Policy-makers have responded to the crisis with a number of innovative policy measures and a desire for better analytic tools to assess this market.¹ In particular, there is a need for econometric tools that help forecast house price corrections. The academic literature has reflected this view; Glaeser and Nathanson (2014, 14) emphasize that it is important to explain the variance of house prices during the periods when house prices “briefly explode and then tumble.” This paper focuses on these extreme episodes.

In this paper, we construct a model to forecast house price corrections in the national housing markets of 18 OECD countries. We focus on large corrections: the (real) national house price index must decline by at least 10 per cent and the correction must last at least four quarters. There are 43 such corrections in our post-1975 sample, which highlights the advantage of an international data set. More importantly for policy-makers, the corrections appear to be triggered by increases in central bank policy rates.

Our modelling approach proceeds in two steps. In the first step, we construct two forecasting variables. The first variable is a simple estimate of the amount of house price overvaluation in each country. Motivated by an asset-pricing framework, the overvaluation is estimated from a panel regression of (real) national house price indexes on per capita, real disposable income and long-term interest rates from each country. The panel regression uses country fixed-effects to capture constant differences.

The second forecasting variable is an estimate of the stance of the central bank’s monetary policy in each country. We estimate this in two ways. The first is the deviation of the short-term interest rate from its Taylor rule level. The second is to construct an explicit forward-looking monetary policy variable. To do this, we decompose long-term (10-year) government bond yields in each of our countries into two components. The first, the expectations component, is the (average) short-term (policy) interest rates that investors expect over the next 10 years. The second is the risk-premium component, which is the extra return required by investors for holding long-term bonds.² When the expectations component is increasing, investors are pricing in their belief that the central bank will be increasing the short-term interest rate. This, in turn, is likely to cause a slowdown in growth and points to increasing funding costs in the future for those with variable-rate mortgages.

In the second step of our analysis, we use both forecasting variables in a panel logit regression model. The model forecasts the likelihood of a house price correction in each of our 18 countries over three forecast horizons: for corrections that start next quarter, corrections that start sometime in the next year and corrections that start sometime in the next two years. We show that the estimated degree of house price overvaluation is able to forecast corrections at all horizons. We also show that there are some advantages to using the decomposition of the long-term interest rate as a predictor. The two components of the yield curve behave differently both before the house price correction and after the

¹See Davis and van Nieuwerburgh (2014) for a survey. For recent work from Bank of Canada staff see Peterson and Zheng (2011), Peterson (2012), Alpanda and Zubairy (2013), and Schembri (2014).

²See Bauer and Diez de los Rios (2012) and the analysis below for further details.

correction has commenced. This behavior would be masked by a simple analysis using the long-term interest rate.

This paper builds on a growing literature that examines the dynamics of an international cross-section of house prices. Ahearne et al. (2005) examine house prices in 18 industrialized economies. They show that house price cycles are correlated across countries and coincide with a peak in economic activity such as inflation and growth. However, they do not use their data to estimate the likelihood of house price corrections, nor do they relate them to risk premiums or monetary policy measures. Croce and Haurin (2009) show how to predict turning points. Agnello and Schuknecht (2011) estimate a panel probit model on 18 countries to estimate the likelihood of normal, boom and bust periods in housing prices. They show that per capita income, interest rates and credit forecast house price boom and bust periods. The global nature of housing markets is examined by Igan and Lungani (2012). Jorda et al. (2014b) use a long sample of international data with alternative exchange rate regimes to estimate the impact of interest rates on house prices. They find that both mortgage credit and interest rates can be used to forecast house price movements. The increase in mortgage credit helps to predict the likelihood of a crisis.

A number of papers have examined the links between monetary policy and house prices. Some of these studies focus on individual countries. Taylor (2007) argues that deviations of policy rates from the Taylor rule are the primary cause of the crisis. Jarociński and Smets (2008) estimate a Bayesian vector autoregression (VAR) on U.S. data. They find that monetary policy shocks explain a large portion of the increase in U.S. house prices. While term spread shocks have a limited impact, they find some evidence that the low, long-term interest rates of the mid-2000s contributed to the boom. Eickmeier and Hofmann (2013) use a factor-augmented VAR to show that monetary policy contributed to the overvaluation of U.S. house prices.

Others argue that monetary policy had a limited impact on house prices. Glaeser, Gottlieb and Gyourko (2010) employ a user cost of credit model to argue that low interest rates had only a modest impact on house prices. Kuttner (2012) argues that monetary policy had a limited role in causing the U.S. crisis and attributes it to low longer-term rates. Our paper adds to this literature by showing the value of using a sophisticated term structure model to decompose long-term interest rates into their two components. The two components in turn provide different information about house price cycles and monetary policy.

Another strand of the literature conducts cross-country panel analyses on the role of credit and crises (e.g., Gourinchas and Obstfeld (2012), Schularick and Taylor (2012), Bordo and Lane (2013), Jorda, Schularick, and Taylor (2013, 2014a and 2014b)).³ Below, we show whether adding credit variables improves the predictive ability of the model.

The goal of this paper is to provide policy-makers with a simple tool to assess the likelihood of a house price crisis. As an example, we provide additional analysis of the Canadian housing market. The Canadian case is challenging, since the market did not experience as large a correction observed by many other countries during the recent crisis.

³Single-country analyses of the role of credit in house price dynamics include Iacoviello (2005), Glaeser, Gottlieb and Gyourko (2010), and Iacoviello and Neri (2010).

Thus, the current question for Canadian policy-makers is to assess the likelihood of a correction against the backdrop of increasing nominal house prices and low policy rates.

In theory, it should be possible to estimate the degree of house price overvaluation and the consequent likelihood of a correction using the data from a single country only. However, it will be difficult to estimate the degree of overvaluation in a given country if the values of homes in the markets are already away from their fundamental values. Regressing one upward-trending series (such as real house prices) on another trending series (such as real per capita income) will always produce a coefficient that can justify most of the current level of valuation. The addition of many other countries, with housing market cycles that may be different from that of Canada, will impose more discipline on the estimation of such a coefficient.

In addition, the estimation of the likelihood of a correction requires sufficient previous data on house price cycles. Since there were only two previous (large) corrections in Canada in our sample period, it would be difficult to determine the current likelihood of a large reversal in prices using Canadian data only. A large amount of structure based on theory would have to be imposed on the model, and it is uncertain how much of this structure would be appropriate.

Thus, our approach assumes that the other countries are “similar enough” to Canada to use their corrections as data points for the model. The other country corrections are somewhat clustered in time, indicating some global aspect to house price dynamics. A country fixed-effects analysis is used throughout to capture constant cross-country differences.

The paper proceeds as follows. The next section presents the data, explains how the correction episodes are calculated and constructs an estimate of house price overvaluation. It also describes how we estimate the monetary policy stance measures along with the credit aggregates. Section 3 presents the details of the econometric model and details the statistical evaluation criteria. The results are presented in Section 4 while Section 5 concludes.

2 Preliminary Analysis

2.1 Data

The quarterly panel data set covers 18 advanced OECD countries and runs from 1975Q1 to 2014Q2. Real and nominal house price and per capita, personal disposable income indices were obtained from the Federal Reserve Bank (FRB) of Dallas. These are seasonally adjusted and rebased to 2005 = 100. FRB Dallas selects national house price series that are most consistent with the Federal Housing Finance Agency’s U.S. house price index, which contains data for existing single-family houses.⁴ They use household disposable income and divide it by the working-age population for each corresponding country to obtain a per capita measure. Real values for the two variables are obtained using the personal consumption expenditure deflator.

⁴FRB Dallas calculates a national house price index for Canada that is a combination of indexes from the University of British Columbia and Royal LePage.

We have also collected a number of macroeconomic series including interest rates (short-term “policy” rates and long-term government bond yields); credit (to the private non-financial sector); output (nominal GDP); and prices (consumer price indices). Data for interest rates, nominal GDP, and consumer prices are obtained from the OECD Economic Outlook or Main Economic Indicators. Short-term interest rates are typically three-month Treasury bills or interbank rates, while long-term rates are 10-year government bond yields. Nominal GDP data are measured in millions of local currency units at market prices, and consumer price indices are rebased to 2005 = 100.

Credit data are collected from the Bank for International Settlements (BIS). The series measure the outstanding amount of credit at the end of each quarter, and cover loans and debt securities. We have obtained credit from all sectors to the private non-financial sector, and credit from domestic banks to the private non-financial sector. The private non-financial sector is defined as non-financial corporations (private and public), households, and non-profit institutions serving households. In order to create a long time series that covers as many countries as possible, the BIS has had to collect data from several sources, which include the financial accounts by institutional sector, the balance sheets of domestic banks, international banking statistics, and the balance sheets of non-bank financial institutions. As a result, some of the data are reported with a different methodology and contain breaks in the series. Therefore, the BIS publishes two data sets – one that is unadjusted, and one that is adjusted for these breaks. We use the adjusted series in our model.⁵

Following the literature, we normalize the two credit series in two ways. First, we construct measures of real credit by normalizing by the consumer price index in each country. We also create ratios that express the total credit outstanding by the country’s (nominal) GDP.

Also included is a U.S. term structure risk premium series from the Baucor-Diez de los Rios (2012) model. This variable serves as a proxy for the global term structure risk premium and is described in more detail below.

2.2 Identification of house price corrections

We follow Agnello and Schuknecht (2011), who use the “triangular methodology” of Harding and Pagan (2002), to identify the duration and magnitude of housing market corrections. Local peaks and troughs are indicated when the first difference of the quarterly log real house price index changes sign. That is, $\Delta p_{j,t} > 0$, $\Delta p_{j,t+1} \leq 0$ is identified as a local peak, while $\Delta p_{j,t} < 0$, $\Delta p_{j,t+1} \geq 0$ is identified as a local trough, where $p_{j,t}$ is the (log) real house price index of country j at time t . The duration of the cycle is measured as the number of quarters from peak to trough, while the magnitude is calculated as the difference between $p_{j,t}$ and $p_{j,t+h}$ where h is the duration in quarters. Due to the number of local housing market cycles in the data, true corrections are identified as those that see a house price decline of at least 10 per cent that last at least four quarters, $h \geq 4$.

⁵Credit data for New Zealand were not available from the BIS, and instead are obtained from the Reserve Bank of New Zealand. The data consist of the sum of M3 institutions’ claims on lending to the private sector (resident and non-resident).

This methodology identifies 43 corrections for all countries in the data set. The start of each correction period is shown in Figure 1. There is some correlation between the start of the corrections across the 18 countries, suggesting that these are not purely country-specific events. Below we show that house prices are related to the level of disposable income and long-term interest rates in each country. In addition, we show that the corrections are triggered in large part by central banks responding to growth and inflationary pressures. Since disposable income, long-term interest rates, growth, and inflation all contain global components, it is not too surprising that the increase and sharp decline in house prices also show cross-country correlations.

Figure 2 displays the real house price index in each country along with the periods that have been identified as corrections. The country with the highest number of corrections is Spain, at six corrections between 1975Q1 and 2014Q2. Denmark has experienced five corrections over its history. Japan records the longest duration of a housing market correction at 61 quarters, or 15 years. Other notable countries with long correction durations are Spain (26 quarters), Germany (25 quarters), Italy (25 quarters) and Sweden (25 quarters).

Canada's historical record shows two such corrections. Prices declined by a total of 30 per cent over a period of six quarters starting in 1981Q3, and by 17 per cent over a one-year period beginning in 1990Q2. For comparison, the United States also saw two housing market corrections. The first occurred in 2006Q4 and lasted seven quarters, and the second began in 2009Q1 and ended five quarters later. During these two periods, the country experienced house price declines of 10 per cent and 14 per cent, respectively.

2.3 Estimated house price overvaluation

The likelihood of a house price correction is likely driven in large part by the current level of house prices relative to some fundamental level. Assessing this degree of house price "overvaluation" is a difficult exercise. It is common to use simple ratios, such as a price-to-rent ratio, to measure the degree of overvaluation. However, understanding time variation in price-to-rent ratios requires a model of the factors underlying the ratio (e.g., Campbell et al., 2009). In addition, the figures presented above suggested that there is some correlation across the corrections in the 18 countries, which suggests that they are likely caused by common factors.

Our approach is to treat houses in each country as an asset. Following a standard asset-pricing approach, we assess the value of the home as the expected discounted value of future cash flows. The cash flows would be the rents, adjusted for taxes and maintenance costs. The discount rate used should be the mortgage interest rate, adjusted for risk and expectations of growth in house values.

However, these data prove difficult to obtain in a cross-country analysis. There are no (reliable) cross-country rent data so we use (log) real, per-capita disposable income in each country j (y_{jt}). The maintained hypothesis is that rents are driven by per-capita economic growth over the long run. An additional problem is that the mortgage rate data that are available do not cover the entire time period of analysis nor all of the countries used. As a result, we assume that the discount rates are proportional to long-term (10-year) government bond yields in each country ($r_{j,t}^{(10)}$). Since houses are long-lived assets, the

discount rate should be proportional to the government long-term bond yield. Constant cross-country differences (e.g., supply of land) will be captured by country fixed-effects.

The house price panel regression model with country fixed-effects is then

$$p_{j,t} = \alpha_{j,0} + \alpha_1 y_{j,t} + \alpha_2 r_{j,t}^{(10)} + \varepsilon_{j,t}^{HP}, \quad (1)$$

where $p_{j,t}$ is the (log) value of the real house price index in country j , $y_{j,t}$ is (log) real per capita disposable income and $r_{j,t}^{(10)}$ is the long-term (10-year) interest rate. Country fixed-effects are captured by $\alpha_{j,0}$. We can then consider the estimated residual $\hat{\varepsilon}_{j,t}^{HP}$ as the deviation of the actual house price index from its predicted value. This will be used as an estimate of the “overvaluation” of the houses in each country.

The regression supports our choice of explanatory variables. The α_1 coefficient is estimated to be 1.271 with a (robust) standard error of 0.0450, while α_2 is estimated to be -0.785 (0.223). Both coefficients are significant.

The Canadian and other country average amounts of overvaluation are shown in Figure 3. The average amount of overvaluation across the other 17 OECD countries (black line) shows considerable variation over time, reaching approximately 15 per cent at the height of the latest boom period. Canadian house prices (red line) were considered to be “fairly” valued in 2004, but are now estimated to be overvalued by slightly over 20 per cent (as of 2014Q2). The interquartile range of the 18 country estimates (the 25th and 75th percentile of overvaluation at each point in time) is shown in dotted lines.

One way to see the relationship between the amount of overvaluation and the typical correction in the data is to use an “event study analysis” where we calculate the average overvaluation before and after the start of the corrections that were shown in Figure 1. The event study graph for the estimated amount of overvaluation in an event window that starts three years before the correction and goes to three years after the correction is shown in Figure 4(a). On average, house prices increase from being 10 per cent overvalued to approximately 21 per cent overvalued before entering a correction. Although we have chosen a correction to be a decline of at least 10 per cent over four quarters, the figure indicates that, on average, house prices fall by approximately 20 per cent over the subsequent three years.

2.4 Monetary policy variables

We construct two measures of the monetary policy stance of the central bank in our sample of countries. The first measure is the deviation of the short-term interest rate from its Taylor rule level. We estimate the Taylor rule level of the interest rate in each country by constructing both inflation and output gaps. For the inflation gap, we use a backward-looking moving-average filter to get a smoothed estimate of past inflation over the previous four quarters. We then assume that, prior to the commencement of widespread inflation-targeting rules in 1995, central banks were trying to reduce the existing levels of inflation. We thus set the inflation target to be 0.95 times the backward-looking moving average. Starting in 1995, we assume that all central banks are following a 2 per cent inflation target.

We also calculate an output gap. We apply the Hodrick-Prescott filter (with a smoothing parameter of 1600) to (log) per capita disposable income in each country. We then

use the deviation of the level of income from its filtered value as an estimate of the output gap.⁶

Finally, we combine both of the gap measures into a Taylor rule level of the short-term interest rate ($r_{j,t}^{TR}$):

$$r_{j,t}^{TR} = r_{j,t}^N + 0.5 * (\Delta\pi_{j,t} - \Delta\pi_{j,t}^*) + 0.5 * (y_{j,t} - y_{j,t}^*), \quad (2)$$

where $r_{j,t}^N$ is the neutral (nominal) rate of interest in country j , $\Delta\pi_{j,t}$ is the actual inflation rate in country j , $y_{j,t}$ is the actual level of real, per capita income, and starred values indicate a target level. The neutral rate is set equal to the inflation target plus an assumed 2 per cent real growth rate. We can then use the estimated deviation of the short-term interest rate from its Taylor rule level as an indicator of the monetary policy stance of the country, $\hat{\varepsilon}_{j,t}^{TR} = r_{j,t} - r_{j,t}^{TR}$.

We may examine the role of monetary policy around a typical house price correction using the event study analysis. Figures 4(b) and 4(c) present the output and inflation gaps, respectively, in event time. The estimated Taylor rule deviation is presented in Figure 4(d). There is a clear pattern to the output gap with actual per capita income levels rising above the estimated potential levels until the start of the house price correction. There is more noise in the estimated measures of the inflation gaps, but we note that the levels are above zero up to the start of the correction. While the estimate is noisy, Figure 4(d) shows that, on average, central banks have tightened policy rates in the three-year period prior to the correction.

The tightening of monetary policy has an effect on the economy. House prices decline, with the average amount of overvaluation going to zero (Figure 4(a)). The output gap shrinks considerably. While the inflation gap is more persistent, it also declines during the correction period, reaching negative levels. This clear pattern of tightening prior to the correction in the event time analysis suggest that the model is doing a good job in capturing the monetary policy stance of the central banks.⁷

The second estimate of the monetary policy stance of the central bank uses an estimated term structure risk premium from Bauer and Diez de los Rios (2012). That paper constructs a multi-country affine term structure model with unspanned macroeconomic risks. The authors use the model to decompose the long-term (10-year) interest rate ($r_{j,t}^{(10)}$) from country j into an expectations component and a term structure risk-premium component:

$$r_{j,t}^{(10)} = r_{j,t}^{EC} + tp_{j,t}. \quad (3)$$

The expectations component,

$$r_{j,t}^{EC} = \frac{1}{10} \sum_{h=1}^{10} E_t r_{j,t+h-1}^{(1)},$$

is the expected average value of the short-term policy rate over the next 10 years. The term premium component ($tp_{j,t}$) is the extra return required by international investors

⁶We use personal disposable income in our estimate of the output gap to reduce the number of variables in future versions of the model.

⁷If the model were doing a poor job, its residuals from the cross-section of countries should be random noise when averaged in event time.

for holding a 10-year bond. Under the assumption that global sovereign bond markets are integrated, the term premium is compensation for holding a global (systematic) risk. All country-specific term premia would be idiosyncratic and diversified away (have a zero price of risk) in global portfolios.

Unfortunately, the Bauer-Diez model was estimated using the bond market data of only four of the countries in our sample. However, we can use the assumption of global market integration to construct an estimated term premium component for all 18 countries. If global bond markets are integrated, then the term premium in any country j will be linear in the term premium on U.S. government bonds:

$$tp_{j,t} = \gamma_j \cdot tp_{U.S.,t}. \quad (4)$$

Under this assumption, a simple projection of the long-term interest rate on the U.S. term premium component allows us to recover the estimated country j risk premium (4), $\hat{tp}_{j,t} = \hat{\gamma}_j \cdot tp_{U.S.,t}$. Given the definition in (3), the difference between the yield in country j and our estimated level of the risk premium is then the country j expectations component, $\hat{r}_{j,t}^{EC} = r_{j,t} - \hat{\gamma}_j \cdot tp_{U.S.,t}$.

The results of this decomposition for the expectations component and the risk premium in event time are shown in Figures 4(e) and 4(f), respectively. The expectations component is high ahead of the start of the house price correction. We note that it is quite forward looking, since it increases two years prior to the start of the correction and remains high. Once the correction starts, and economic growth begins to slow, the central bank lowers the short-term policy rate. The expectations component declines a bit ahead of the turning point, as the market anticipates future central bank moves. Once the correction period has commenced, the expectations component falls by approximately 200 basis points, anticipating that central banks will have to reduce policy rates.

As explained in Bauer and Diez de los Rios (2012), the risk premium component is countercyclical and thus rises after the beginning of the house price correction, when the economy is weak. Figure 4(f) shows that the premium is low ahead of the corrections, which may cause some to seek for yield in the house market. Although beyond the scope of this paper, this may indicate another reason for examining term structure risk-premiums as an indicator of optimal monetary policy rules (e.g., see Stein (2014)).

3 Model Estimation and Evaluation

3.1 Panel logit analysis

To assess the likelihood of a house price correction, we incorporate the degree of house price overvaluation and a monetary policy stance variable into a panel logit model:

$$P(Y_{j,t+h} = 1 \mid M_m) = F(\beta_{j,0} + \beta x_{j,t}), \quad (5)$$

where $P(Y_{j,t+h} = 1 \mid M_m)$ is the probability that a house price correction $Y_{j,t+h}$ starts sometime between dates t and $t+h$ in country j , F is the cumulative logistic function,

$$F(\beta_{j,0} + \beta x_{j,t}) = \frac{\exp\{\beta_{j,0} + \beta x_{j,t}\}}{1 + \exp\{\beta_{j,0} + \beta x_{j,t}\}}, \quad (6)$$

and $x_{j,t}$ is a set of forecasting variables under model M_m . The country fixed-effects are captured by the $\beta_{j,0}$ coefficients. The β coefficients on the explanatory variables are assumed to be the same across all countries. In our tests, we use the selected forecasting variables to evaluate the likelihood of a correction occurring in one quarter ($Y_{j,t+1}$), sometime in the next year ($Y_{j,t+4}$), and sometime in the next two years ($Y_{j,t+8}$).

We evaluate a number of models that differ in their choice of explanatory variables. The simplest model is to assume that there is no time variation in the likelihood of a correction (i.e., we use only country fixed-effects, $\beta_{j,0}$). This produces the unconditional likelihood of a house price correction for each country that is the same as the frequency of the corrections in the historical data. We label this model the unconditional model and denote it M_0 .

We use the deviation of the house price index from its fundamental value ($\hat{\varepsilon}_{j,t}^{HP}$) in all of the other models. We next incorporate one of our two measures of the monetary policy stance of the central bank into our analysis. For the first set of models we use the deviation of the short-term interest rate from its Taylor rule value ($\hat{\varepsilon}_{j,t}^{TR}$), while for the second we use the two components of the long-term interest rate ($\hat{r}_{j,t}^{EC}$ and $\hat{p}_{j,t}$). We also assess whether the credit measures that have been useful in the previous literature cited above add additional explanatory power.

Estimation is by maximum likelihood. We follow Thompson (2011) and report all standard errors that are clustered both on the country level and across time.

3.2 Forecasting metrics

Evaluating the projected probabilities from a logit model has proved difficult to summarize using a single measure. This will be especially true of evaluating turning points in asset markets. Since housing markets display some properties of asset prices, this will be true in the current application as well. The intuition behind the problem is simple. Consider the typical logit model analysis that attempts to assess the likelihood of a decline in asset prices. As risk-free profit opportunities in financial markets appear to be rare, the estimated probabilities should be far away from their lower and upper bounds of zero and one, respectively. For example, an estimated value of zero suggests that the asset is guaranteed to rise in value, while an estimated value of one signals the opposite. Both situations, if true, would be a violation of no arbitrage pricing. The key, therefore, will be to assess the likelihood of house price declines that are above zero, yet far away from one.

We thus employ a number of evaluation statistics. The first is the pseudo R^2 statistic from Campbell et al. (2008). We calculate the log likelihood of the unconditional model (country fixed-effects only) and denote it L_0 . We can then compare this to the likelihood of an alternative model (M_1) which includes additional explanatory variables (L_1):

$$R^2 = 1 - \frac{L_1}{L_0}.$$

In addition, we can evaluate the statistical significance of the explanatory variables via a traditional Wald test. This test produces a chi-squared test statistic that we report along with its asymptotic marginal significance level (P -value).

One statistic of interest is the hit rate of the model. Let $\hat{P}(Y_{j,t+h} = 1 \mid M_m)$ denote the estimated likelihood of a house price correction using model m . The hit rate is defined as

$$HIT = \frac{1}{N} \sum_j \sum_t Y_{j,t+h} * 1[\hat{P}(Y_{j,t+h} = 1 \mid M_m) \geq \hat{P}(Y_{j,t+h} = 1 \mid M_0)] \\ + (1 - Y_{j,t+h}) * 1[\hat{P}(Y_{j,t+h} = 1 \mid M_m) < \hat{P}(Y_{j,t+h} = 1 \mid M_0)], \quad (7)$$

where $1[x]$ is the indicator function that takes the value of one if condition x is true. We calculate the aggregate hit rate of the model (across all 18 countries in sample) by calculating the sample analog of (7) using a country fixed-effects regression where the standard errors are robust to both country and time fixed-effects. In essence, we are applying the Diebold and Mariano (1995) test statistic methodology to a panel data set. We are thus able to report a robust P -value associated with the test that the hit rate equals zero. We note that this hit rate differs from those traditionally presented, since we use the unconditional model's probabilities of a correction as the cut-off values to determine when the conditional models are delivering a signal of an impending correction.

We can use our panel data set version of the Diebold and Mariano (1995) test methodology to calculate the differences between models using a number of other loss functions. For example, the Brier test statistic for evaluating probability forecasts use the quadratic probability score (QPS), a quadratic loss function:

$$QPS(M_m) = \frac{1}{N} \sum_j \sum_t 2 * (Y_{j,t+h} - \hat{P}(Y_{j,t+h} = 1 \mid M_m))^2. \quad (8)$$

Our panel test method with double-clustered standard errors allows us to calculate this statistic for a single model M_m (as in (8)) as well as comparing the QPS statistics for the difference between the conditional and unconditional models:

$$QPS(M_m - M_0) = \frac{1}{N} \sum_j \sum_t 2 * (Y_{j,t+h} - \hat{P}(Y_{j,t+h} = 1 \mid M_m))^2 \\ - 2 * (Y_{j,t+h} - \hat{P}(Y_{j,t+h} = 1 \mid M_0))^2. \quad (9)$$

We also report the P -value associated with this test statistic.

Finally, we can compare the forecasting performance of the model using the area under the receiver operating characteristic curve (AUROC). This has become a popular method to summarize the likelihood of making correct decisions (see, e.g., Schularick and Taylor (2012)). The area varies between 0.50 and 1.00, with the latter measure indicating that the model can distinguish perfectly between correction and non-correction periods. We also perform a model comparisons test of the AUROC on the given model relative to the unconditional model (M_0). This test has a chi-squared test statistic that we report along with its P -value.

4 Results

4.1 Deviations from the Taylor rule

We start by evaluating the ability of the estimated Taylor rule deviations and house price overvaluations to forecast house price corrections. The first columns in Tables 1(a), 1(b) and 1(c) provide the results for the panel logit regression model to forecast house price corrections that occur in the next quarter (Y_{t+1}), sometime in the next year (Y_{t+4}) and sometime in the next two years (Y_{t+8}), respectively.

The coefficient attached to the estimated house price overvaluation rises from 5.988 to 6.952 as the forecast horizon lengthens from one quarter to two years. The coefficients attached to this variable are statistically significant at all horizons. As the degree of house price overvaluation from our simple model increases, there is an increased likelihood of a 10 per cent or greater correction. The estimated overvaluation from our simple model thus aids policy-makers in identifying impending corrections.

The Taylor rule deviations ($\varepsilon_{i,t}^{TR}$) also have good forecast power for crises that commence in the next quarter Y_{t+1} . The estimated coefficient is 11.00, which is statistically significant at the 5 per cent level using double-clustered standard errors. As we increase the forecast horizon to two years (Y_{t+8}), the estimated coefficient increases slightly to 13.99 while retaining its statistical significance. As the policy interest rate increases above its Taylor rule level, the likelihood of the commencement of a house price correction increases. Thus, while the event study graph 4(d) shows that this is a relatively noisy estimator, the statistical results indicate that it does have forecasting power.

Overall, this simple model has relatively good forecasting power. The pseudo- R^2 statistic is 21.8 per cent, and both of the variables are statistically significant according to the standard Wald test that shows a chi squared test statistic above 39. However, tests for the goodness of fit of the model show mixed results. The hit rate (7) is an impressive 69.1 per cent, suggesting that the model is able to discriminate between correction and non-correction periods. As the forecast horizon lengthens, the statistic remains very close to that level, indicating no significant gain in forecast power. Other statistics are not so favorable to the model performance. The QPS statistic (8) actually rises with the forecast horizon from 0.026 for the quarterly forecast to 0.153 at a two-year horizon. The model appears to lose forecast performance as the horizon lengthens, when errors in making forecasts of corrections are evaluated using a quadratic loss.

A better way to judge the model from the perspective of a policy-maker is to evaluate the differences between forecasts from the (conditional) model and forecasts from an unconditional model, M_0 . The Diebold-Mariano test statistic of the difference in quadratic loss (9), is very small and not statistically significant (the P -value of the difference between the two models is only 10.5 per cent) at a quarterly horizon. This indicates that there is no statistically significant difference between the probabilities of the conditional model and those from its unconditional counterpart. However, as the forecast horizon lengthens, the test statistic improves and the marginal significance level falls. The conditional model thus provides statistically significantly better forecasts than the unconditional one at longer horizons.

Finally, we can compare the areas under the receiver operating characteristic (ROC)

curve (AUROC statistics). Relative to the literature, these look large. The AUROC statistics are above 0.8 for all horizons. In previous work on the role of credit in predicting crises (e.g., Jorda, Schularick, and Taylor (2013) or Schularick and Taylor (2012)), the statistics range from 0.6 to 0.7, only reaching the levels shown here for some specifications.

How useful would such a model be to policy-makers who would like to evaluate the likelihood of a house price crisis in the coming quarter? A simple way to answer this question is to compare the increase in probability from the fitted values of the model during the pre- and post-correction periods. The top panel of Table 3 shows the change in the fitted probability during the two-year period leading up to the correction, and in the two-year period subsequent to the correction. A test of difference between the two periods is also shown. The average change is calculated for each country and then averaged across all countries. The standard errors are double clustered with respect to country and time. Using this simple base-case model, the probability of a crisis in the next quarter increases by 1.7 per cent in the two-year period prior to the correction. While it is statistically different from the 1.8 per cent decline that occurs during the post-correction period, it is hard to imagine policy-makers dramatically changing their optimal monetary policy paths for such a small increase.

On the other hand, a completely different picture emerges when we examine the changes in probability of predicting a correction that starts sometime in the next two years. The bottom panel of Table 3 provides these estimates. The estimated probabilities from the base-case model rises by 9.2 per cent during the two-year period leading up to the start of a correction. They in turn fall by 12.4 per cent during the correction period. Figure 4(g) shows that the probabilities reach approximately 32 per cent on average before the start of the corrections.

To see how this model would fare historically, we plot the fitted values in Figure 5. Once again we display the 17-country average using the dark line, with the estimated value for Canada in red. Also shown is the interquartile range across all countries at each point in time. There are large swings in the 17-country average, with the average estimated probability peaking at approximately 25 per cent just prior to the onset of the global house price crisis of 2007-08. The two previous corrections noted above for Canada are evident. We note that the estimated likelihood of a correction (i.e., at least a 10 per cent decline in real house prices) in the Canadian market that starts sometime in the next two years is approximately 20 per cent.⁸

4.2 Two components of the long-term interest rate

The forward-looking measure of the monetary policy stance in each of the countries produces a similar outcome. The first columns of Tables 2(a), 2(b), and 2(c) show the ability of the estimated house price overvaluation and the two components of the long-term interest rate to forecast house price corrections that start next quarter, sometime in the next year and sometime in the next two years, respectively.

The estimated coefficients on the degree of house price overvaluation are close to their

⁸The standard errors associated with this in-sample prediction are large, so the 95 per cent confidence interval of this estimate ranges from 10 to 30 per cent.

values shown in Table 1. They also retain their statistical significance. The expectations component, which represents investors' forecasts of future policy rates, has strong predictive power for corrections at all forecast horizons. At the quarterly forecast horizon, the coefficient is 12.78 and is significant at the 10 per cent level. As the forecast horizon increases, the coefficient increases in size, reaching 19.90 (5 per cent significance) at the two-year horizon. As the market increases its assessment of future policy rate increases, the likelihood of a house price correction rises. We note again that this measure is relatively forward looking. The event study analysis (Figure 4(e)) shows that this component increases in a period that starts three years before the correction, rising by about 100 basis points. The expectations component remains elevated up to the start of the correction, at which point it rapidly declines.

Of interest, the term structure risk premium in each country proves not to be a statistically significant predictor of house price crises. Indeed the coefficient changes sign as the forecast horizon increases, decreasing from 6.899 at the quarterly horizon to -5.241 at a two-year horizon. The coefficient is not significant at any horizon. An analysis of the risk premium in event time reveals why (Figure 4(f)). While it does display some variation, the estimated risk premium remains low ahead of the start of the correction. The estimated output gap shows that these are boom times and investor risk aversion is likely to be low. Once the correction has started, the risk premium increases rapidly, rising by over 100 basis points on average, as investors become more risk averse.

We can relate this finding to three strands of the existing literature. First, it supports the analysis found in Bauer and Diez de los Rios (2012) and others, who find that term structure risk-premiums are strongly countercyclical. The event study here shows that the countercyclical nature of the term structure risk premium may be related to the housing cycle.

Second, the analysis may explain why previous studies that use long-term interest rates have not found them to be statistically significant predictors of crises or housing market cycles (e.g., Kuttner (2012)). The two components of the long-term interest rate move in opposite directions before and after the start of the house price correction. These offsetting movements would tend to diminish the role of the total long-term interest rate during these times.

Third, the analysis provides support for those who advocate using risk premiums to provide an assessment for financial stability (e.g., Stein (2014)). Here the risk premiums are used to obtain a better measure of investor expectations of future policy rates. These expectations increase long before the beginning of the house price correction and remain elevated. It may be, however, that more advanced techniques could capture the "low for long" aspect of the risk premiums themselves and use this as a predictor of house price corrections and other phenomena of interest.

Once again we may use the statistical criteria to evaluate the in-sample fit of the model. The pseudo- R^2 statistics are similar in value to those from the Taylor rule model. The estimated hit rate remains relatively flat, rising from 71.2 per cent at the quarterly horizon to 72.7 per cent at the two-year horizon. The QPS statistic rises moderately with the forecast horizon from 0.027 for one quarter ahead to 0.155 for two years ahead. While this would indicate a deterioration in forecast performance, the difference between

this statistic and the unconditional measure (9) actually improves. In addition, the area beneath the ROC curve increases from 0.828 to 0.864. Thus, there are moderate increases in forecast accuracy using the statistical metrics.

As above, an examination of the trend of the probabilities around the corrections reveals a better way to interpret the model results. The top panel of Table 4 shows the change in probabilities of a house price correction starting in the next quarter, during a two-year event window on both sides of the start of the correction. The results show that the estimated probability of a crisis over the next quarter increases by 1.6 per cent over a two-year window prior to the crisis. Although this is statistically significant it would be difficult for policy-makers to rely on such a small degree of variation to change policies to avoid a crisis. The quarterly probabilities decrease by 2.1 per cent in the two-year period after the crisis. Thus, the average difference in probabilities between the pre- and post-crisis periods is 3.8 per cent, which is statistically significant with a P -value < 0.001 .

In contrast, it is much easier to notice the changes in probabilities as the associated forecast horizon lengthens. When the probabilities are calculated for a two-year horizon, they increase by a total of 9.2 per cent (statistically significant) in the two-year period prior to the crisis. Once the crisis has arrived, the probabilities decline by 16.1 per cent, resulting in a statistically significant difference of 25.3 per cent in the two-year windows pre- and post-crisis. Such a stronger signal would be easier for policy-makers to interpret. These results mirror those for the model that uses the Taylor rule deviation.

We can put the current likelihood of a house price correction into context by examining the likelihood of a crash around the 43 correction "events" that were shown in Figure 1. Figure 4(h) shows an event study of the likelihood of a correction starting sometime in the next two years. The slow increase in the likelihood of a crisis matches that of the Taylor rule model. Table 4 shows that the increase in probabilities at the three horizons is similar to their Taylor rule counterparts.

4.3 Credit measures as predictors

As mentioned in the introduction, a number of papers have used measures of credit to forecast banking, credit and foreign exchange crises. Here we assess their ability to improve the models used to forecast house price corrections. As mentioned above, we have normalized the two credit series (total and bank) by both the consumer price index and by the level of GDP. We include four lags (i.e., one year) of the series to examine any changes in the dynamics.

The second and third columns of Table 1 show the coefficients on the real total and bank credit series, respectively, in the panel logit regression model that includes the Taylor rule deviation as a predictor. It is interesting to note that coefficients on the real credit series increase in size and significance as the forecast horizon increases. Indeed, all of the coefficients are individually significant in the model that assesses the likelihood of a correction starting sometime in the next two years (Table 1(c)). The coefficients are all positive, indicating that an increase in credit to the non-financial private sector aids in the forecasts of corrections. Without further structure, however, it is not clear why the series have this effect. It could be that homeowners become overextended so that the demand for credit must decline in the correction period. It could also be that lenders

change the desire to supply credit as they anticipate a downturn in the economy. We note that the coefficient attached to the Taylor rule deviation becomes insignificant when the real credit series are included.

The fourth and fifth columns of Table 1 show the coefficients on the credit series normalized by GDP. These variables are not statistically significant predictors of corrections at any of the horizons examined.

The real credit series also enter significantly when the two components of the long-term interest rate are used as predictors, especially at the two-year horizon (second and third columns of Table 2). In contrast to the Taylor rule specification, the forward-looking measure of policy interest rates (the expectations component) remains statistically significant at all horizons. The term premium remains insignificant.

While the real credit series are statistically significant predictors, they do not appear to improve the in-sample fit of the model by a large amount. Focusing on the two-year horizon for the model in Table 2(c), we see that the hit rates actually decrease when the real credit variables are included. However, the other statistics show a small improvement over the base-case model. The QPS test statistic (8) is smaller and the difference between the QPS statistics for this model and the unconditional one (9) becomes more negative. The AUROC statistics rise slightly.

While the coefficients are statistically significant and some of the statistics indicate a better in-sample fit, it is not certain that the dynamics of total real credit would aid policy-makers in this application. The bottom panel of Table 4 shows that the estimated likelihood of a correction would increase by 10.8 per cent in the two-year period prior to the start of the correction. This is only a small gain compared to the 9.2 per cent increase displayed by the base-case model with the two components of the long-term interest rate.

5 Final Remarks

In this paper, we construct a panel logit regression model that attempts to forecast house price corrections in 18 OECD countries. The model incorporates a simple measure of the overvaluation of the houses in each country along with two different estimates of the monetary policy stance of the central bank in each country. We also include some measures of the quantity of credit that have been recently issued in each country.

There are a number of conclusions of interest to policy-makers. First, the relatively simple way of assessing house price overvaluation has good forecasting power for subsequent corrections. The variable is significant in all specifications and at all horizons. Second, while the two methods of estimating the monetary policy stance of the central banks produce similar results, the method of extracting a global risk premium from the long-term interest rate has some advantages. The expectations component is forward looking and rises well in advance of the corrections. This may be quite useful to policy-makers today who face the zero lower bound on current policy rates while the long-term rates incorporate expectations of future rate increases.

Third, there is a distinct forecast-horizon aspect to the results. Attempting to forecast a house price decline that is going to start in the next quarter is extremely difficult. The signals from this modelling approach are very weak and would be engulfed by the noise

of the estimates. In contrast, when we construct the likelihood of a correction occurring sometime in the next two years, the method produces clearer results. The increase in the estimated probability of the corrections is much larger. We note again that such likelihoods will always remain difficult to interpret, since values near zero or one are unlikely to occur.

Finally, this paper provides evidence that price measures forecast house price corrections better than measures of the quantity of credit. While the latter have proved quite popular in forecasting a variety of crises, it would be interesting to see whether price-based measures would be helpful in that regard as well.

References

- [1] Agnello, L. and L. Schuknecht. 2011. "Booms and Busts in Housing Markets: Determinants and Implications," *Journal of Housing Economics* 20, pp.171-190.
- [2] Ahearne, A.G., J. Ammer, B.M. Doyle, L.S. Kole, and R.F. Martin. 2005. "House Prices and Monetary Policy: A Cross-Country Study," Board of Governors of the Federal Reserve System, International Finance Discussion Paper 841.
- [3] Alpanda, S. and S. Zubairy. 2013. "Housing and Tax Policy," Bank of Canada working paper 2013-33.
- [4] Baron, M. and W. Xiong. 2014. "Credit Expansions and Neglected Crash Risk." Princeton University working paper.
- [5] Bauer, G.H. and A. Diez de los Rios. 2012. "An International Dynamic Term Structure Model with Economic Restrictions and Unspanned Risks." Bank of Canada working paper 2012-5.
- [6] Bordo, M.D. and J.L. Lane. 2013. "Does Expansionary Monetary Policy Cause Asset Price Booms; Some Historical and Empirical Evidence," NBER working paper series no. 19585.
- [7] Campbell, S.D., M.A. Davis, J. Gallin, and R.F. Martin. 2009. "What Moves Housing Markets: A Variance Decomposition of the Rent-Price Ratio," *Journal of Urban Economics*, vol. 66, no. 2, pp. 90-102.
- [8] Campbell, J.Y., J. Hilscher, and J. Szilagyi. 2008. "In Search of Distress Risk," *Journal of Finance* vol. 58, no. 6, pp. 2899-2939.
- [9] Croce, R.M., and D.R. Haurin. 2009. "Predicting Turning Points in the Housing Market," *Journal of Housing Economics* 18, pp.281-293.
- [10] Davis, M.A. and S. Van Nieuwerburgh. 2014. "Housing, Finance and the Macroeconomy." Department of Real Estate, University of Wisconsin-Madison working paper.
- [11] Diebold, F.X. and R.S. Mariano. 1995. "Comparing Predictive Accuracy," *Journal of Business and Economic Statistics* 13, pp. 253-263.
- [12] Dynan, K.E. and D.L. Kohn. 2007. "The Rise in U.S. Household Indebtedness: Causes and Consequences," Federal Reserve Board Finance and Economics Discussion Series 2007-37.
- [13] Eickmeier, S., and B. Hofmann. 2013. "Monetary Policy, Housing Booms and Financial (Im)balances," *Macroeconomic Dynamics* 17, pp. 830-860.
- [14] Glaeser, E.L., J.D. Gottlieb and J. Gyourko. 2010. "Can Cheap Credit Explain the Housing Boom," NBER working paper series no. 16230.

- [15] Glaeser, E.L. and C.G. Nathanson. 2014. "Housing Bubbles." NBER working paper 20426.
- [16] Gourinchas, P.O. and M. Obstfeld. 2012. "Stories of the Twentieth Century for the Twenty-First," *American Economic Journal: Macroeconomics* 4, pp. 226-265.
- [17] Harding, D. and A. Pagan. 2002. "Dissecting the cycle: a methodological investigation," *Journal of Monetary Economics* 49, pp. 365-381.
- [18] Iacoviello, M. 2005. "House Prices, Borrowing Constraints and Monetary Policy in the Business Cycle," *American Economic Review*, pp. 739-764.
- [19] Iacoviello, M. and S. Neri. 2010. "Housing Market Spillovers: Evidence from an Estimated DSGE Model," *American Economic Journal: Macroeconomics* 2, April 2010, 125-164.
- [20] Igan, D. and P. Loungani. 2012. "Global Housing Cycles," IMF Working Paper WP/12/17.
- [21] Jarociński, M. and F.R. Smets. 2008. "House Prices and the Stance of Monetary Policy," Federal Reserve Bank of St. Louis *Review*, July/August, pp. 339-365.
- [22] Jorda, O., M. Schularick and A.M. Taylor. 2013. "When Credit Bites Back." *Journal of Money, Credit and Banking*, vol. 45, no. 2, pp. 3-28.
- [23] Jorda, O., M. Schularick and A.M. Taylor. 2014a. "Financial Crises, Credit Booms and External Imbalances: 140 Years of Lessons." *IMF Economic Review*, June 2011, 59(2): 340-378
- [24] Jorda, O., M. Schularick and A.M. Taylor. 2014b. "Betting the House." Federal Reserve Bank of San Francisco working paper.
- [25] Kuttner, K.N. 2012. "Low Interest Rates and Housing Bubbles: Still No Smoking Gun," working paper, William College.
- [26] Ludvigson, S.C. 2007. "Discussion of Housing and Consumer Behavior." Proceedings of the Federal Reserve Bank of Kansas City's symposium on "Housing, Housing Finance, and Monetary Policy," Jackson Hole, Wyoming.
- [27] Peterson, B. 2012. "Fooled by Search: Housing Prices, Turnover and Bubbles." Bank of Canada working paper 2012-3.
- [28] Peterson, B. and Y. Zheng. 2011. "Medium-Term Fluctuations in Canadian House Prices." Bank of Canada *Review*, Winter 2011-12.
- [29] Schembri, L. 2014. "Housing Finance in Canada: Looking Back to Move Forward." *National Institute Economic Review* (November): R45-R57.
- [30] Schularick, M. and A. M. Taylor. 2012. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008," *American Economic Review* 102 pp. 1029-61.

- [31] Stein, J.C. 2014. "Incorporating Financial Stability Considerations into a Monetary Policy Framework." Board of Governors of the Federal Reserve System, Washington D.C.
- [32] Taylor, J.B. 2007. "Housing and Monetary Policy," NBER working paper series no. 13682.
- [33] Thompson, S.B. 2011. "Simple Formulas for Standard Errors that Cluster by both Firm and Time." *Journal of Financial Economics* 99, 1-10.

Figure 1
Start of House Price Corrections

Notes: the figure shows the start dates of the 43 housing market corrections (a decline in real house prices of at least 10 per cent that lasts at least four quarters) in all 18 OECD countries from 1975Q1 to 2014Q2. The corrections for Canada are displayed in red.

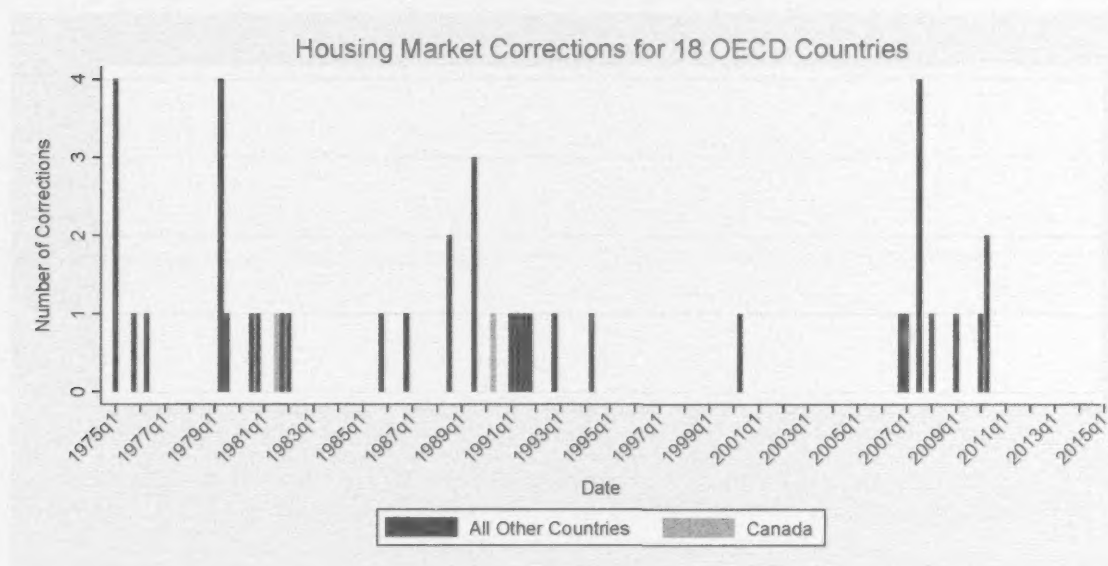


Figure 2
Duration of House Price Corrections

Notes: The figure shows the log real house price index and the housing market corrections (a decline in real house prices of at least 10 per cent that lasts at least four quarters) in all 18 OECD countries from 1975Q1 to 2014Q2.

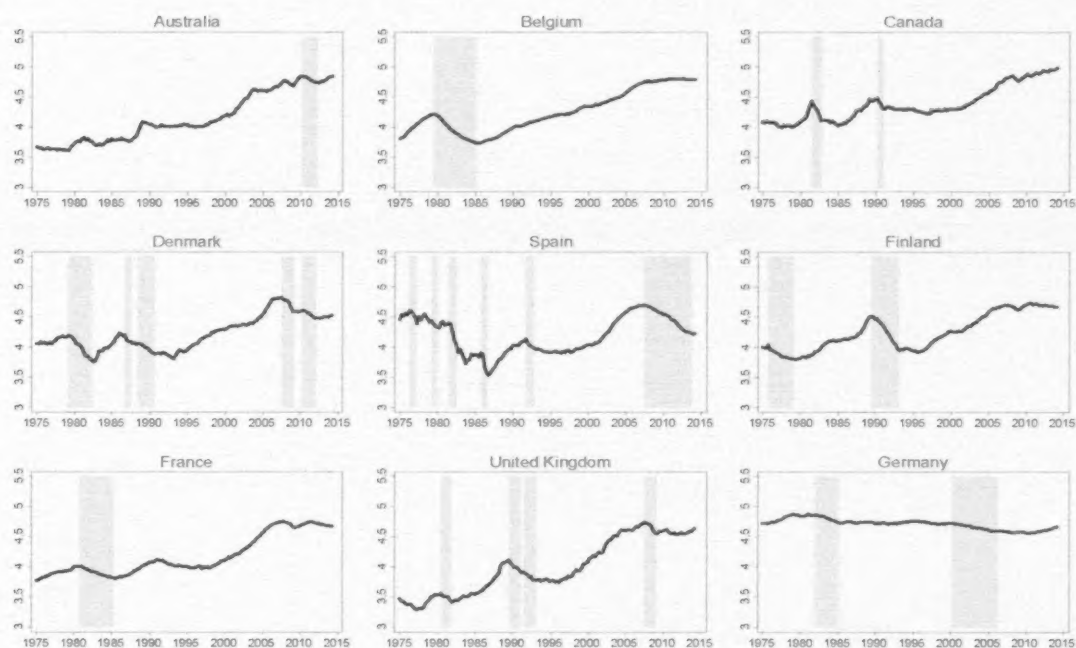


Figure 2, continued
House Price Corrections

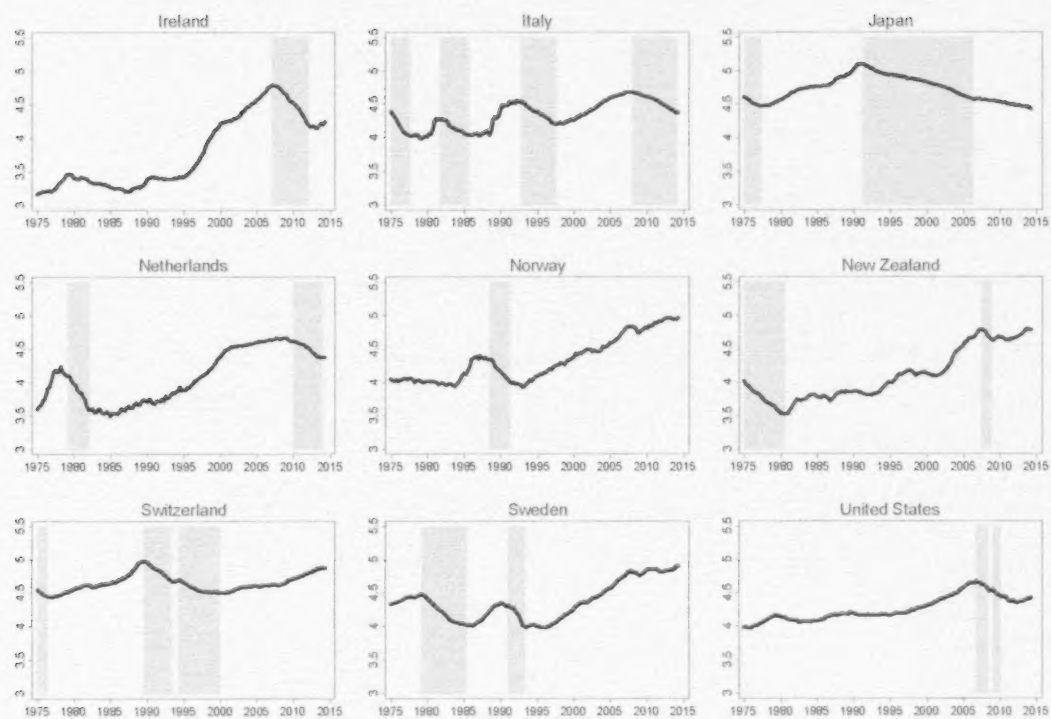


Figure 3
Estimated Level of House Price Overvaluation

Notes: The figure shows the estimated level of house price overvaluation for Canada (red line) and the average value of the 17 other OECD countries (black line). Also shown is the interquartile range (the 25th and 75th highest amounts of overvaluation across all 18 countries at each point in time) in dotted lines. The fundamental value of the house price index comes from a panel regression model where the real house price index is regressed on real, per capita disposable income and the long-term government bond yield in each country. The estimated degree of overvaluation is the residual from the regression. Country fixed effects are used.

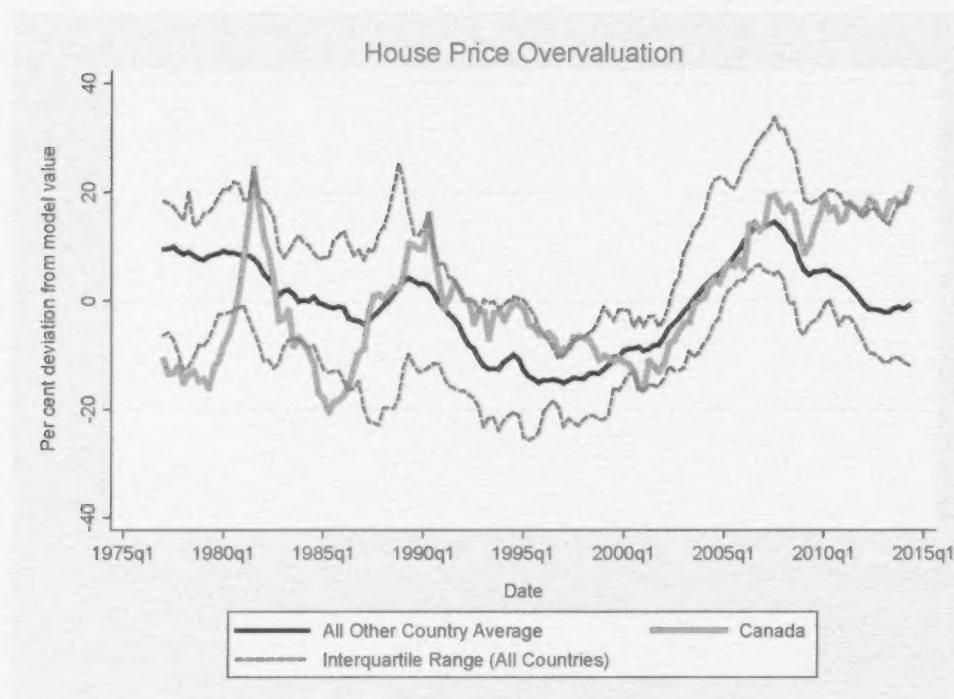


Figure 4(a)**Estimated Level of House Price Overvaluation in Event Time**

Notes: The figure shows the estimated level of house price overvaluation averaged across the 43 corrections that have occurred in the 18 OECD countries. The line shows the average value during an event window that runs from three years before to three years after the start of each house price correction. The fundamental value of the house price index comes from a panel regression model where the real house price index is regressed on real, per capita disposable income and the long-term government bond yield. Country fixed effects are used. The estimated amount of overvaluation is the residual from the panel regression.

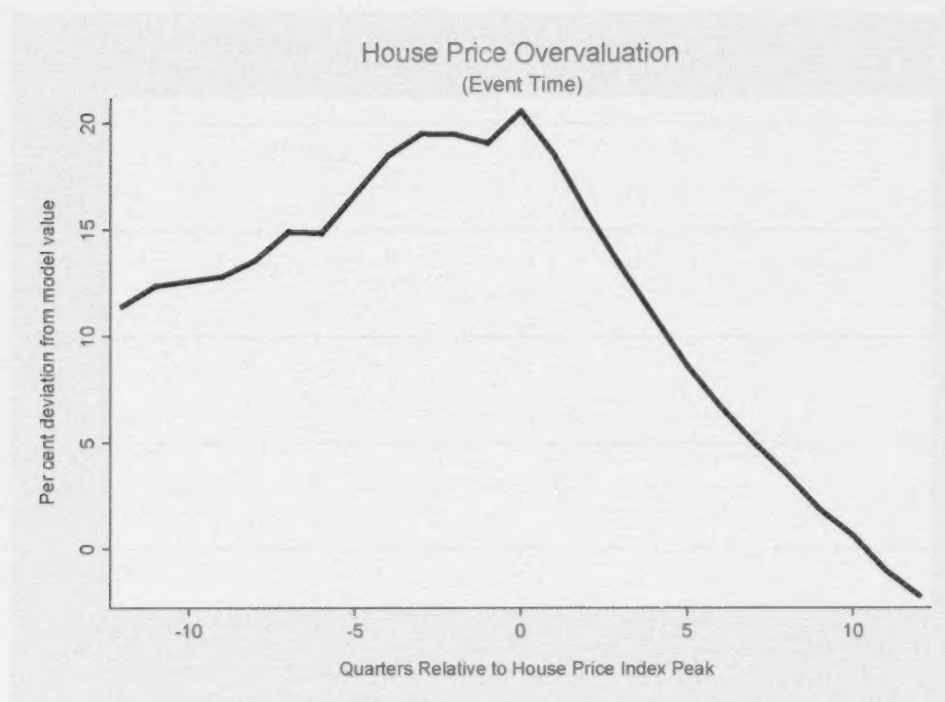


Figure 4(h)**Estimated Output Gap in Event Time**

Notes: The figure shows the estimated level of the output gap averaged across the 43 corrections that have occurred in the 18 OECD countries. The line shows the average value during an event window that runs from three years before to three years after the start of each house price correction. The output gap is the difference between the actual level of real, per capita disposable income and the value estimated from a Hodrick-Prescott filtered value with a smoothing coefficient of 1600.

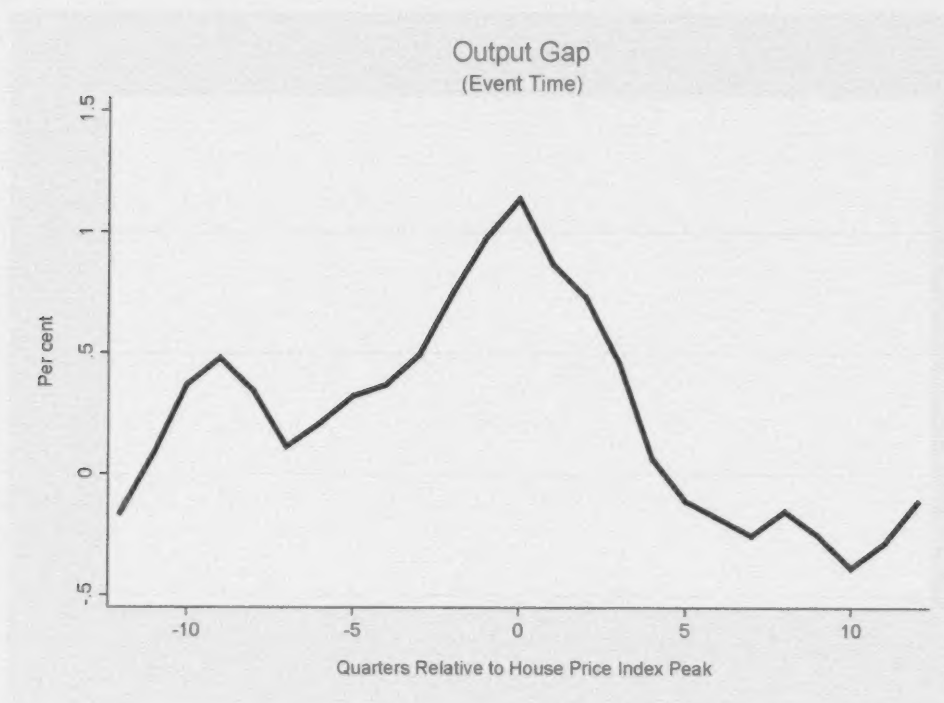


Figure 4(c)
Estimated Inflation Gap in Event Time

Notes: The figure shows the estimated level of the inflation gap averaged across the 43 corrections that have occurred in the 18 OECD countries. The line shows the average value during an event window that runs from three years before to three years after the start of each house price correction. The gap is the difference between the actual level of inflation and a target level. Prior to 1995, the target level of inflation is set equal to the previous quarter's inflation rate times 0.95. After 1995, the target level is set equal to 2 per cent in each country.

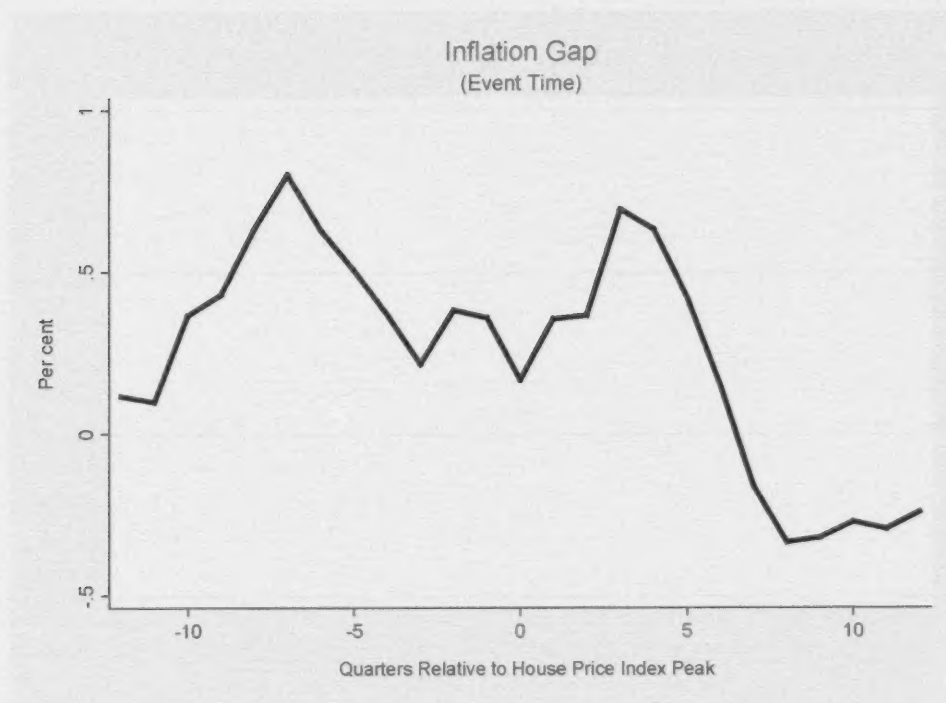


Figure 4(d)**Estimated Deviation from the Taylor Rule in Event Time**

Notes: The figure shows the estimated level of the deviation from the Taylor rule averaged across the 43 corrections that have occurred in the 18 OECD countries. The line shows the average value during an event window that runs from three years before to three years after the start of each house price correction. The estimated Taylor rule level of the interest rate is a weighted combination of the output and inflation gaps as described in the text. The deviation is the difference between the actual short-term interest rate and the estimated Taylor rule rate.

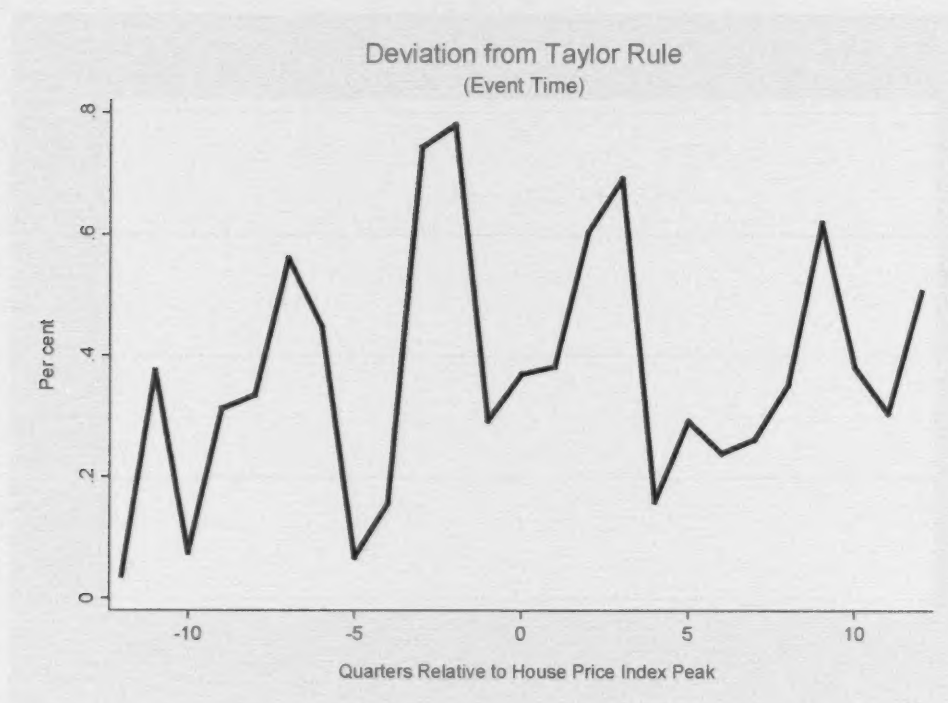


Figure 4(e)**Estimated Expectations Component of the Long-Term Interest Rate in Event Time**

Notes: The figure shows the estimated level of the expectations component of the long-term interest rate averaged across the 43 corrections that have occurred in the 18 OECD countries. The line shows the average value during an event window that runs from three years before to three years after the start of each house price correction. The expectations component is the residual from a projection of the long-term interest rate in each country on the estimated U.S. term structure risk premium from Bauer and Diez de los Rios (2012).

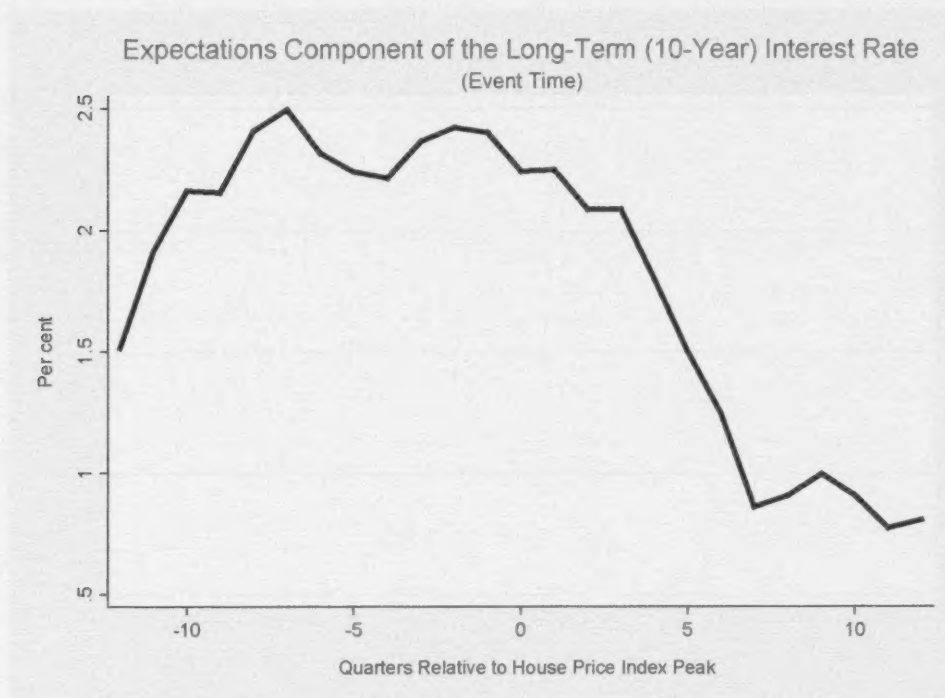


Figure 4(f)**Estimated Term Premium Component of the Long-Term Interest Rates in Event Time**

Notes: The figure shows the estimated level of the term premium component of the long-term interest rate averaged across the 43 corrections that have occurred in the 18 OECD countries. The line shows the average value during an event window that runs from three years before to three years after the start of each house price correction. The term premium component for each country is estimated by projecting the long-term interest rate on the U.S. term structure risk premium from Bauer and Diez de los Rios (2012).

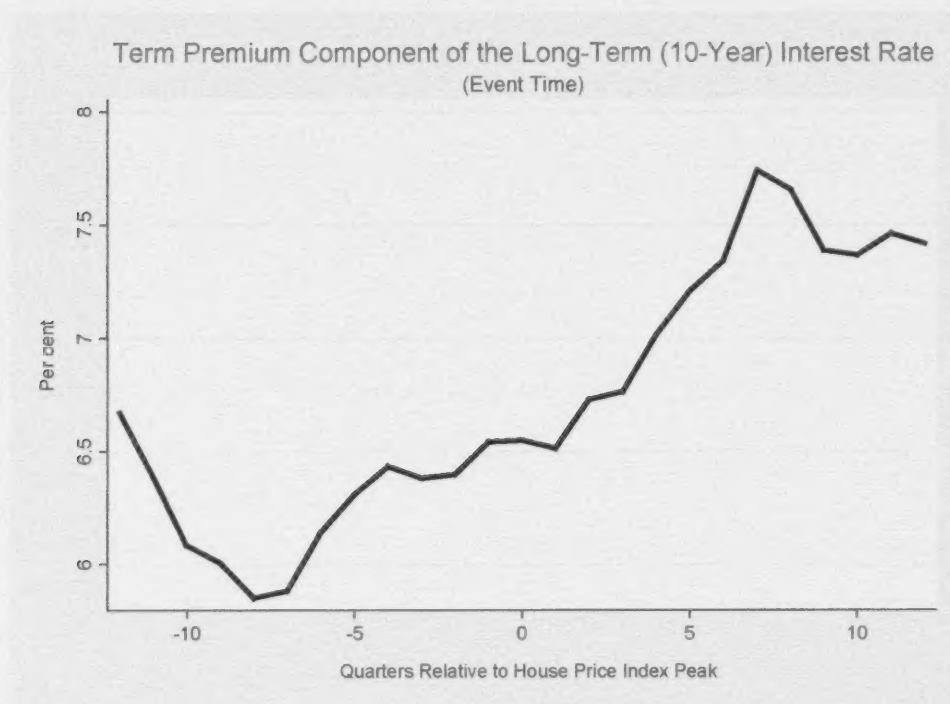


Figure 4(g)

**Estimated Likelihood of a House Price Correction Starting Sometime in the Next Two Years Using
Taylor Rule Deviations in Event Time**

Notes: The figure shows the estimated likelihood of a house price correction starting sometime in the next two years averaged across the 43 corrections that have occurred in the 18 OECD countries. The line shows the average value during an event window that runs from three years before to three years after the start of each house price correction. The likelihood comes from a panel logit regression model that uses deviations from the Taylor rule and the estimated amount of house price overvaluation as explanatory variables. Country fixed effects are used.

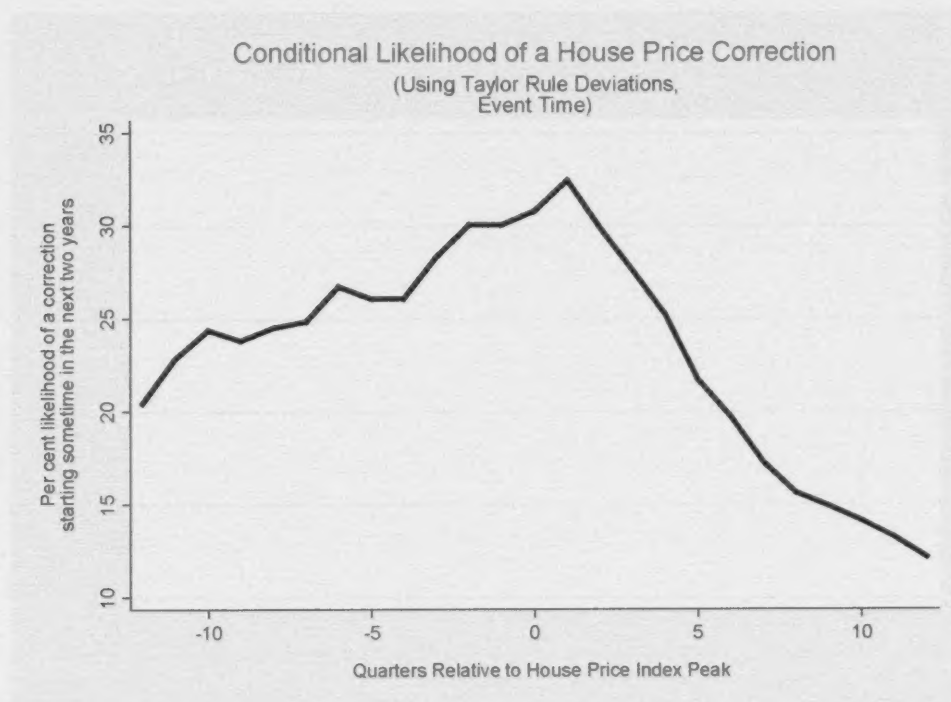


Figure 4(h)

Estimated Likelihood of a House Price Correction Starting Sometime in the Next Two Years Using the Two Components of the Long-Run Interest Rates in Event Time

Notes: The figure shows the estimated likelihood of a house price correction starting sometime in the next two years averaged across the 43 corrections that have occurred in the 18 OECD countries. The line shows the average value during an event window that runs from three years before to three years after the start of each house price correction. The likelihood comes from a panel logit regression model that uses the two components of the long-term interest rate and the estimated amount of house price overvaluation as explanatory variables. Country fixed effects are used.

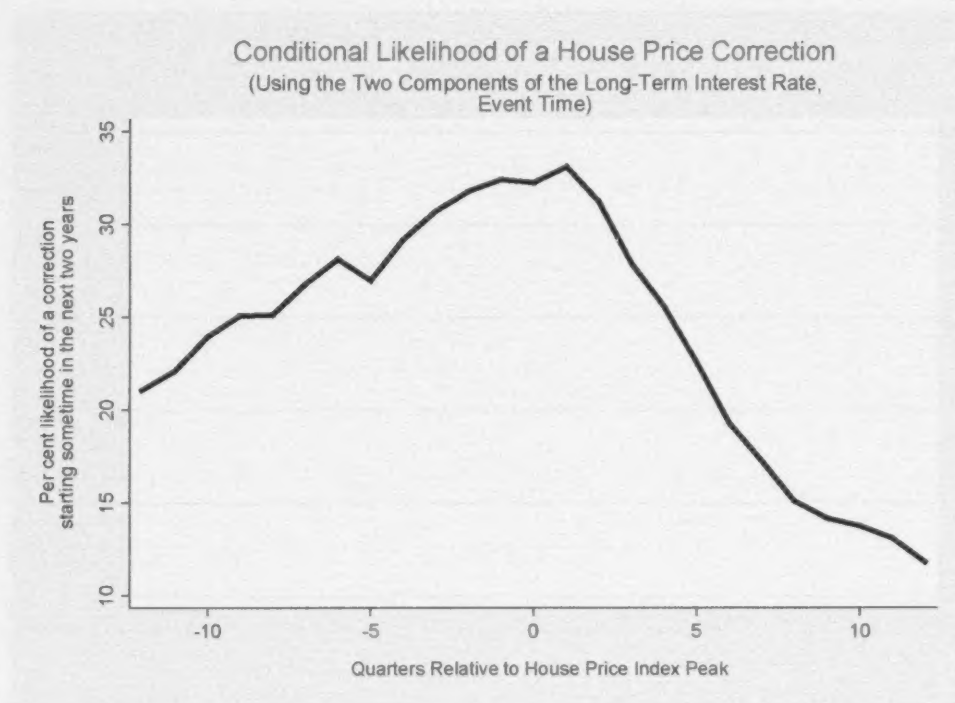


Figure 5
Estimated Likelihood of a House Price Correction Starting Sometime in the Next Two Years Using Taylor Rule Deviations

Notes: The figure shows the estimated likelihood of a house price correction starting sometime in the next two years for Canada (red line) and the average value of the 17 other OECD countries (black line). Also shown is the interquartile range (the 25th and 75th highest levels of likelihood across all 18 countries at each point in time) in dotted lines. The likelihood comes from a panel logit regression model that uses deviations from the Taylor rule and the estimated amount of house price overvaluation as explanatory variables. Country fixed effects are used.

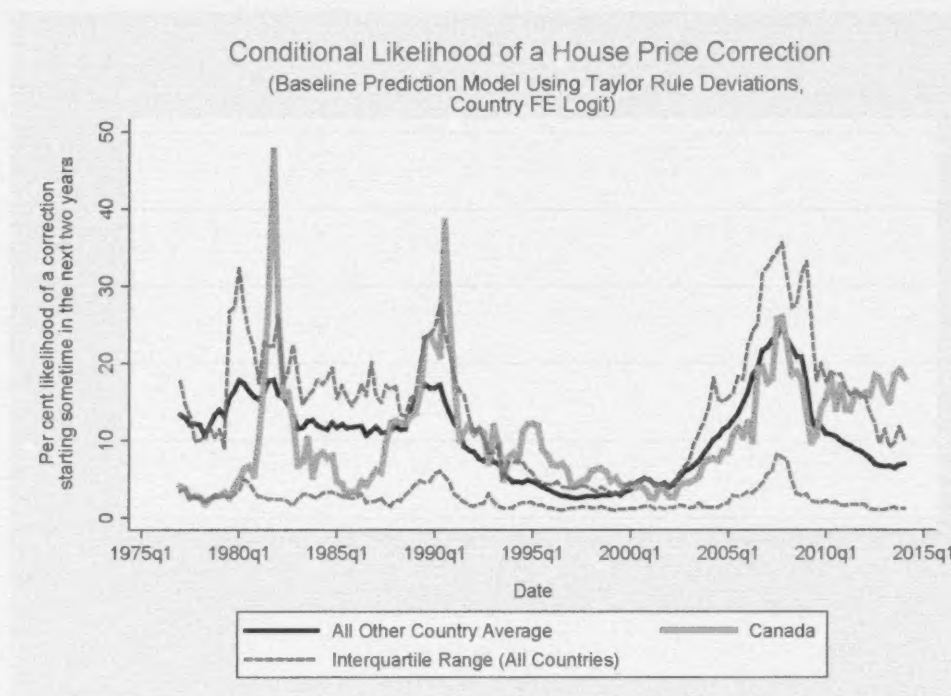


Figure 6

Estimated Likelihood of a House Price Correction Starting Sometime in the Next Two Years Using the Two Components of the Long-Tun Interest Rate

Notes: The figure shows the estimated likelihood of a house price correction starting sometime in the next two years for Canada (red line) and the average value of the 17 other OECD countries (black line). Also shown is the interquartile range (the 25th and 75th highest levels of likelihood across all 18 countries at each point in time) in dotted lines. The likelihood comes from a panel logit regression model that uses the two components of the long-term interest rate and the estimated amount of house price overvaluation as explanatory variables. Country fixed effects are used.

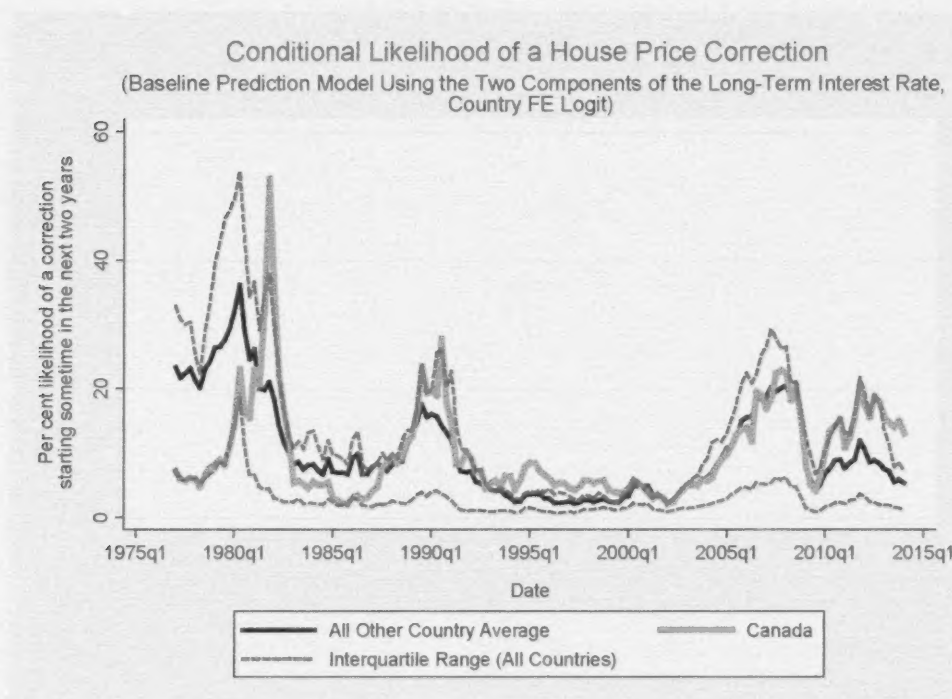


Table 1(a)

Results of Panel Logit Regression Models Using Deviations from the Taylor Rule to Evaluate the Likelihood of a House Price Correction Starting in the Next Quarter

Notes: The table shows the estimated coefficients and summary statistics from the panel logit regression models that evaluate the likelihood of a house price correction starting in the next quarter. The models use the estimated amount of house price overvaluation (ε^{HP}) and the deviation of the short-term interest rate from its Taylor rule level (ε^{TR}) as an estimate of the monetary policy stance of the central bank. Other measures of credit are then added as regressors. Country fixed effects (parameters not shown) are used. The standard errors shown in round brackets are robust to clustering at both the country level and over time (Thompson 2011). The stars indicate marginal significance levels (***) $P < 0.01$, ** $P < 0.05$, * $P < 0.1$). The summary statistics are explained in the text.

	Base case	Base case + Total (real) credit (all)	Base case + Total (real) credit (banks)	Base case + Total credit/GDP (all)	Base case + Total credit/GDP (banks)
ε^{HP}	5.988*** (1.117)	5.747*** (0.967)	5.550*** (0.886)	5.970*** (1.113)	5.767*** (1.027)
ε^{TR}	11.00** (5.299)	7.493 (5.400)	8.343 (5.303)	10.77** (5.351)	10.24* (5.254)
$\Delta tcred_{t-1}$		-3.703 (10.69)			
$\Delta tcred_{t-2}$		2.229 (12.65)			
$\Delta tcred_{t-3}$		5.217 (9.782)			
$\Delta tcred_{t-4}$		23.24* (13.31)			
$\Delta bcred_{t-1}$			0.629 (12.54)		
$\Delta bcred_{t-2}$			-0.592 (11.47)		
$\Delta bcred_{t-3}$			3.483 (11.47)		
$\Delta bcred_{t-4}$			13.45 (9.078)		
$\Delta tcred/GDP_{t-1}$				0.340* (0.177)	
$\Delta tcred/GDP_{t-2}$				0.303 (0.225)	
$\Delta tcred/GDP_{t-3}$				0.223 (0.148)	
$\Delta tcred/GDP_{t-4}$				0.440** (0.182)	
$\Delta bcred/GDP_{t-1}$					0.384** (0.164)
$\Delta bcred/GDP_{t-2}$					0.222 (0.242)
$\Delta bcred/GDP_{t-3}$					0.277* (0.162)
$\Delta bcred/GDP_{t-4}$					0.395** (0.195)

Observations	2,719	2,667	2,567	2,667	2,567
Pseudo R^2	0.218	0.234	0.245	0.219	0.239
Chi-sq. stat.	39.016	8.119	4.299	6.768	6.754
<i>P</i> -value	0.000	0.001	0.065	0.000	0.079
Hit rate	0.691	0.680	0.653	0.671	0.642
(s.e.)	(0.016)	(0.034)	(0.006)	(0.016)	(0.004)
QPS stat.	0.026	0.026	0.025	0.027	0.026
(s.e.)	(0.003)	(0.008)	(0.006)	(0.033)	(0.033)
QPS diff. stat.	-0.001	-0.001	-0.001	-0.001	-0.001
(s.e.)	(0.000)	(0.009)	(0.000)	(0.004)	(0.000)
<i>P</i> -value	0.105	0.040	0.367	0.111	0.001
AUROC	0.822	0.814	0.812	0.820	0.815
(s.e.)	(0.032)	(0.001)	(0.003)	(0.004)	(0.004)
Chi-sq. test	13.223	11.525	11.086	12.973	12.047
<i>P</i> -value	0.000	0.000	0.001	0.000	0.001

Table 1(b)

Results of Panel Logit Regression Models Using Deviations from the Taylor Rule to Evaluate the Likelihood of a House Price Correction Starting Sometime in the Next Year

Notes: The table shows the estimated coefficients and summary statistics from the panel logit regression models that evaluate the likelihood of a house price correction starting sometime in the next year. The models use the estimated amount of house price overvaluation (ε^{HP}) and the deviation of the short-term interest rate from its Taylor rule level (ε^{TR}) as an estimate of the monetary policy stance of the central bank. Other measures of credit are then added as regressors. Country fixed effects (parameters not shown) are used. The standard errors shown in round brackets are robust to clustering at both the country level and over time (Thompson 2011). The stars indicate marginal significance levels (*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$). The summary statistics are explained in the text.

	(1)	(2)	(3)	(4)	(5)
	Base case	Base case + Total (real) credit (all)	Base case + Total (real) credit (banks)	Base case + Total credit/GDP (all)	Base case + Total credit/GDP (banks)
ε^{HP}	6.737*** (1.090)	6.440*** (0.991)	6.176*** (0.918)	6.717*** (1.085)	6.483*** (1.018)
ε^{TR}	14.81*** (5.552)	10.45 (6.732)	10.81* (6.406)	14.60*** (5.647)	13.84** (5.555)
Δcred_{t-1}		6.592 (5.323)			
Δcred_{t-2}		6.738 (4.829)			
Δcred_{t-3}		13.69*** (4.072)			
Δcred_{t-4}		9.838** (4.551)			
$\Delta \text{bcred}_{t-1}$			4.195 (4.416)		
$\Delta \text{bcred}_{t-2}$			3.652 (3.893)		
$\Delta \text{bcred}_{t-3}$			9.939*** (3.256)		
$\Delta \text{bcred}_{t-4}$			7.994 (5.428)		
$\Delta \text{cred}/\text{GDP}_{t-1}$				0.370** (0.172)	
$\Delta \text{cred}/\text{GDP}_{t-2}$				0.355** (0.159)	
$\Delta \text{cred}/\text{GDP}_{t-3}$				0.381** (0.152)	
$\Delta \text{cred}/\text{GDP}_{t-4}$				0.313* (0.173)	
$\Delta \text{bcred}/\text{GDP}_{t-1}$					0.366** (0.172)
$\Delta \text{bcred}/\text{GDP}_{t-2}$					0.347** (0.160)
$\Delta \text{bcred}/\text{GDP}_{t-3}$					0.370** (0.163)
$\Delta \text{bcred}/\text{GDP}_{t-4}$					0.307 (0.188)

Observations	2,719	2,667	2,567	2,667	2,567
Pseudo R^2	0.221	0.239	0.253	0.223	0.242
Chi-sq. stat.	38.268	6.451	4.613	3.252	6.380
<i>P</i> -value	0.000	0.092	0.000	0.000	0.000
Hit rate	0.693	0.681	0.654	0.673	0.651
(s.e.)	(0.014)	(0.003)	(0.017)	(0.013)	(0.017)
QPS stat.	0.090	0.088	0.086	0.091	0.087
(s.e.)	(0.006)	(0.006)	(0.002)	(0.002)	(0.014)
QPS diff. stat.	-0.010	-0.013	-0.011	-0.010	-0.009
(s.e.)	(0.002)	(0.015)	(0.017)	(0.013)	(0.002)
<i>P</i> -value	0.000	0.000	0.000	0.000	0.041
AUROC	0.830	0.828	0.826	0.827	0.823
(s.e.)	(0.017)	(0.018)	(0.020)	(0.015)	(0.013)
Chi-sq. test	50.322	47.463	47.100	50.656	49.247
<i>P</i> -value	0.000	0.000	0.202	0.000	0.000

Table 1(c)

Results of Panel Logit Regression Models Using Deviations from the Taylor Rule to Evaluate the Likelihood of a House Price Correction Starting Sometime in the Next Two Years

Notes: The table shows the estimated coefficients and summary statistics from the panel logit regression models that evaluate the likelihood of a house price correction starting sometime in the next two years. The models use the estimated amount of house price overvaluation (ε^{HP}) and the deviation of the short-term interest rate from its Taylor rule level (ε^{TR}) as an estimate of the monetary policy stance of the central bank. Other measures of credit are then added as regressors. Country fixed effects (parameters not shown) are used. The standard errors shown in round brackets are robust to clustering at both the country level and over time (Thompson 2011). The stars indicate marginal significance levels (*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$). The summary statistics are explained in the text.

	(1)	(2)	(3)	(4)	(5)
	Base case	Base case + Total (real) credit (all)	Base case + Total (real) credit (banks)	Base case + Total credit/GDP (all)	Base case + Total credit/GDP (banks)
ε^{HP}	6.952*** (1.233)	6.617*** (1.126)	6.243*** (1.044)	6.922*** (1.229)	6.670*** (1.174)
ε^{TR}	13.99** (6.36C)	8.521 (7.672)	7.903 (7.559)	13.80** (6.442)	12.91** (6.373)
$\Delta tcred_{t-1}$		12.18*** (4.628)			
$\Delta tcred_{t-2}$		12.02*** (4.604)			
$\Delta tcred_{t-3}$		12.18** (5.483)			
$\Delta tcred_{t-4}$		11.69*** (4.116)			
$\Delta bcred_{t-1}$			9.647** (3.815)		
$\Delta bcred_{t-2}$			9.268*** (3.595)		
$\Delta bcred_{t-3}$			10.77*** (4.071)		
$\Delta bcred_{t-4}$			13.05*** (4.361)		
$\Delta tcred/GDP_{t-1}$				0.372** (0.187)	
$\Delta tcred/GDP_{t-2}$				0.348** (0.176)	
$\Delta tcred/GDP_{t-3}$				0.334* (0.172)	
$\Delta tcred/GDP_{t-4}$				0.281 (0.188)	
$\Delta bcred/GDP_{t-1}$					0.399** (0.189)
$\Delta bcred/GDP_{t-2}$					0.383** (0.179)
$\Delta bcred/GDP_{t-3}$					0.371** (0.181)
$\Delta bcred/GDP_{t-4}$					0.340* (0.190)

Observations	2,719	2,667	2,567	2,667	2,567
Pseudo R^2	0.220	0.251	0.273	0.222	0.241
Chi-sq. stat.	34.653	8.873	19.189	4.647	4.627
P-value	0.000	0.000	0.000	0.098	0.000
Hit rate	0.690	0.695	0.672	0.669	0.650
(s.e.)	(0.013)	(0.013)	(0.031)	(0.022)	(0.008)
QPS stat.	0.153	0.148	0.143	0.154	0.149
(s.e.)	(0.009)	(0.031)	(0.012)	(0.009)	(0.013)
QPS diff. stat.	-0.029	-0.037	-0.033	-0.030	-0.027
(s.e.)	(0.003)	(0.012)	(0.004)	(0.022)	(0.021)
P-value	0.000	0.000	0.000	0.000	0.000
AUROC	0.830	0.838	0.839	0.827	0.822
(s.e.)	(0.012)	(0.005)	(0.033)	(0.021)	(0.022)
Chi-sq. test	92.197	98.921	95.587	92.339	89.061
P-value	0.000	0.000	0.000	0.000	0.099

Table 2(a)

Results of Panel Logit Regression Models Using the Two Components of the Long-Term Interest Rate to Evaluate the Likelihood of a House Price Correction Starting in the Next Quarter

Notes: The table shows the estimated coefficients and summary statistics from the panel logit regression models that evaluate the likelihood of a house price correction starting in the next quarter. The models use the estimated amount of house price overvaluation (ε^{HP}), and the two components of the long-term interest rate (the expectations component (r^{EC}), which acts as a measure of the monetary policy stance of the central bank, and the term premium component (tp)). Other measures of credit are then added as regressors. Country fixed effects (parameters not shown) are used. The standard errors shown in round brackets are robust to clustering at both the country level and over time (Thompson 2011). The stars indicate marginal significance levels (***) $P < 0.01$, (**) $P < 0.05$, (*) $P < 0.1$. The summary statistics are explained in the text.

	(1) Base case	(2) Base case + Total (real) credit (all)	(3) Base case + Total (real) credit (banks)	(4) Base case + Total credit/GDP (all)	(5) Base case + Total credit/GDP (banks)
ε^{HP}	5.335*** (1.387)	5.285*** (1.045)	5.075*** (0.994)	5.487*** (1.377)	5.290*** (1.287)
r^{EC}	12.78* (7.189)	17.02** (7.121)	15.57** (6.887)	13.11* (7.064)	12.92* (7.108)
tp	6.899 (7.081)	8.411 (7.342)	9.149 (7.035)	7.247 (6.838)	7.426 (6.784)
$\Delta tcred_{t-1}$		1.824 (10.89)			
$\Delta tcred_{t-2}$		4.659 (11.00)			
$\Delta tcred_{t-3}$		9.881 (9.216)			
$\Delta tcred_{t-4}$		25.75** (12.49)			
$\Delta bcred_{t-1}$			4.945 (11.76)		
$\Delta bcred_{t-2}$			0.675 (10.22)		
$\Delta bcred_{t-3}$			6.850 (10.39)		
$\Delta bcred_{t-4}$			16.46* (8.767)		
$\Delta tcred/GDP_{t-1}$				0.402** (0.173)	
$\Delta tcred/GDP_{t-2}$				0.362* (0.202)	
$\Delta tcred/GDP_{t-3}$				0.324** (0.136)	
$\Delta tcred/GDP_{t-4}$				0.490*** (0.187)	
$\Delta bcred/GDP_{t-1}$					0.428*** (0.164)
$\Delta bcred/GDP_{t-2}$					0.305 (0.195)
$\Delta bcred/GDP_{t-3}$					0.351** (0.156)
$\Delta bcred/GDP_{t-4}$					0.449** (0.192)

Observations	2,808	2,680	2,580	2,684	2,584
Pseudo R^2	0.180	0.235	0.244	0.210	0.231
Chi-sq. stat.	16.045	11.963	6.414	7.856	7.765
P -value	0.001	0.000	0.000	0.128	0.000
Hit rate	0.712	0.693	0.660	0.674	0.645
(s.e.)	(0.014)	(0.019)	(0.008)	(0.005)	(0.017)
QPS stat.	0.027	0.026	0.026	0.027	0.026
(s.e.)	(0.003)	(0.001)	(0.003)	(0.004)	(0.003)
QPS diff. stat.	0.000	-0.001	-0.001	-0.001	-0.001
(s.e.)	(0.000)	(0.011)	(0.008)	(0.005)	(0.000)
P -value	0.157	0.013	0.056	0.000	0.127
AUROC	0.828	0.831	0.830	0.832	0.830
(s.e.)	(0.030)	(0.003)	(0.030)	(0.018)	(0.030)
Chi-sq. test	13.367	12.611	12.692	13.699	13.186
P -value	0.000	0.000	0.170	0.000	0.000

Table 2(b)

Results of Panel Logit Regression Models Using the Two Components of the Long-Term Interest Rate to Evaluate the Likelihood of a House Price Correction Starting Sometime in the Next Year

Notes: The table shows the estimated coefficients and summary statistics from the panel logit regression models that evaluate the likelihood of a house price correction starting sometime in the next year. The models use the estimated amount of house price overvaluation (ε^{HP}), and the two components of the long-term interest rate (the expectations component (r^{EC}), which acts as a measure of the monetary policy stance of the central bank, and the term premium component (tp)). Other measures of credit are then added as regressors. Country fixed effects (parameters not shown) are used. The standard errors shown in round brackets are robust to clustering at both the country level and over time (Thompson 2011). The stars indicate marginal significance levels (*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$). The summary statistics are explained in the text.

	(1) Base case	(2) Base case + Total (real) credit (all)	(3) Base case + Total (real) credit (banks)	(4) Base case + Total credit/GDP (all)	(5) Base case + Total credit/GDP (banks)
ε^{HP}	5.992*** (1.340)	5.913*** (1.284)	5.621*** (1.185)	5.975*** (1.459)	5.782*** (1.397)
r^{EC}	14.32** (7.229)	20.30*** (7.289)	18.19*** (7.029)	15.05** (7.322)	14.81** (7.299)
tp	4.098 (8.261)	6.584 (8.898)	7.004 (8.388)	4.192 (8.196)	4.688 (8.088)
$\Delta tcred_{t-1}$		11.93** (5.637)			
$\Delta tcred_{t-2}$		11.16** (5.285)			
$\Delta tcred_{t-3}$		17.22*** (3.538)			
$\Delta tcred_{t-4}$		13.50*** (3.015)			
$\Delta bcred_{t-1}$			8.376* (4.395)		
$\Delta bcred_{t-2}$			6.647 (4.276)		
$\Delta bcred_{t-3}$			12.32*** (2.589)		
$\Delta bcred_{t-4}$			10.66*** (2.955)		
$\Delta tcred/GDP_{t-1}$				0.453*** (0.173)	
$\Delta tcred/GDP_{t-2}$				0.426*** (0.165)	
$\Delta tcred/GDP_{t-3}$				0.466*** (0.157)	
$\Delta tcred/GDP_{t-4}$				0.425** (0.168)	
$\Delta bcred/GDP_{t-1}$					0.441** (0.173)
$\Delta bcred/GDP_{t-2}$					0.413** (0.163)
$\Delta bcred/GDP_{t-3}$					0.450*** (0.163)
$\Delta bcred/GDP_{t-4}$					0.414** (0.173)

Observations	2,808	2,680	2,580	2,684	2,584
Pseudo R^2	0.188	0.253	0.261	0.217	0.236
Chi-sq. stat.	23.154	24.922	23.483	6.836	6.848
<i>P</i> -value	0.000	0.000	0.000	0.000	0.000
Hit rate	0.704	0.689	0.662	0.670	0.645
(s.e.)	(0.014)	(0.017)	(0.019)	(0.014)	(0.019)
QPS stat.	0.093	0.087	0.086	0.093	0.090
(s.e.)	(0.006)	(0.016)	(0.015)	(0.006)	(0.002)
QPS diff. stat.	-0.009	-0.015	-0.011	-0.009	-0.008
(s.e.)	(0.002)	(0.004)	(0.005)	(0.019)	(0.015)
<i>P</i> -value	0.000	0.000	0.000	0.001	0.001
AUROC	0.851	0.852	0.849	0.850	0.847
(s.e.)	(0.014)	(0.028)	(0.003)	(0.017)	(0.016)
Chi-sq. test	63.105	56.592	57.481	64.251	63.246
<i>P</i> -value	0.000	0.000	0.000	0.000	0.000

Table 2(c)

Results of Panel Logit Regression Models Using the Two Components of the Long-Term Interest Rate to Evaluate the Likelihood of a House Price Correction Starting Sometime in the Next Two Years

Notes: The table shows the estimated coefficients and summary statistics from the panel logit regression models that evaluate the likelihood of a house price correction starting sometime in the next two years. The models use the estimated amount of house price overvaluation (ε^{HP}), and the two components of the long-term interest rate (the expectations component (r^{EC}), which acts as a measure of the monetary policy stance of the central bank, and the term premium component (tp)). Other measures of credit are then added as regressors. Country fixed effects (parameters not shown) are used. The standard errors shown in round brackets are robust to clustering at both the country level and over time (Thompson 2011). The stars indicate marginal significance levels (***) $P < 0.01$, (**) $P < 0.05$, (*) $P < 0.1$). The summary statistics are explained in the text.

	(1)	(2)	(3)	(4)	(5)
	Base case	Base case + Total (real) credit (all)	Base case + Total (real) credit (banks)	Base case + Total credit/GDP (all)	Base case + Total credit/GDP (banks)
ε^{HP}	6.201*** (1.297)	6.172*** (1.324)	5.835*** (1.214)	6.285*** (1.377)	6.080*** (1.333)
r^{EC}	19.90** (8.094)	26.39*** (8.515)	24.59*** (8.180)	21.18** (8.346)	20.72** (8.270)
tp	-5.241 (9.612)	-2.330 (10.29)	-1.475 (9.853)	-5.058 (9.512)	-4.285 (9.365)
$\Delta tcred_{t-1}$		16.96*** (4.441)			
$\Delta tcred_{t-2}$		15.83*** (4.546)			
$\Delta tcred_{t-3}$		15.56*** (5.089)			
$\Delta tcred_{t-4}$		15.07*** (3.896)			
$\Delta bcred_{t-1}$			13.76*** (3.524)		
$\Delta bcred_{t-2}$			11.83*** (3.384)		
$\Delta bcred_{t-3}$			12.25*** (3.377)		
$\Delta bcred_{t-4}$			14.71*** (2.872)		
$\Delta tcred/GDP_{t-1}$				0.473** (0.190)	
$\Delta tcred/GDP_{t-2}$				0.449** (0.183)	
$\Delta tcred/GDP_{t-3}$				0.466*** (0.178)	
$\Delta tcred/GDP_{t-4}$				0.434** (0.186)	
$\Delta bcred/GDP_{t-1}$					0.486** (0.191)
$\Delta bcred/GDP_{t-2}$					0.467** (0.185)
$\Delta bcred/GDP_{t-3}$					0.480*** (0.185)
$\Delta bcred/GDP_{t-4}$					0.463** (0.190)

Observations	2,808	2,680	2,580	2,684	2,584
Pseudo R^2	0.215	0.292	0.307	0.241	0.259
Chi-sq. stat.	46.140	25.314	43.741	6.196	6.496
<i>P</i> -value	0.000	0.000	0.000	0.000	0.000
Hit rate	0.727	0.715	0.694	0.699	0.674
(s.e.)	(0.013)	(0.016)	(0.010)	(0.016)	(0.004)
QPS stat.	0.155	0.142	0.139	0.156	0.150
(s.e.)	(0.009)	(0.041)	(0.008)	(0.038)	(0.010)
QPS diff. stat.	-0.028	-0.045	-0.039	-0.031	-0.028
(s.e.)	(0.004)	(0.006)	(0.005)	(0.036)	(0.035)
<i>P</i> -value	0.000	0.000	0.000	0.000	0.000
AUROC	0.864	0.874	0.875	0.865	0.861
(s.e.)	(0.010)	(0.009)	(0.039)	(0.004)	(0.014)
Chi-sq. test	139.141	140.364	137.250	146.663	142.833
<i>P</i> -value	0.000	0.000	0.000	0.000	0.039

Table 3
Average Change in Probability of House Price Correction Using Taylor Rule Deviations and other
Explanatory Variables during Pre- and Post-Correction Periods

Note: The table shows the average change in probability during a two-year window prior to the start of the house price correction ("pre-correction average") and during the two-year period following the start of the correction ("post-correction average"). Also shown is the average difference between the two periods along with the marginal significance level of a statistical test of the difference ("*P*-value"). The probabilities are the fitted values from the panel logit models shown in Table 1 that use the estimated deviation of the Taylor rule as a measure of the monetary policy stance of the central banks. The logit models probabilities are calculated for three forecast horizons: house price corrections starting next quarter, house price corrections starting sometime in the next year and house price corrections starting sometime in the next two years. The standard errors shown in round brackets are robust to clustering at both the country level and over time (Thompson 2011).

	(1)	(2)	(3)	(4)	(5)
	Base case	Base case + Total (real) credit (all)	Base case + Total (real) credit (banks)	Base case + Total credit/GDP (all)	Base case + Total credit/GDP (banks)
One Quarter					
Pre-correction average	0.017	0.022	0.017	0.017	0.016
(s.e.)	(0.004)	(0.017)	(0.033)	(0.004)	(0.015)
Post-correction average	-0.018	-0.035	-0.024	-0.018	-0.017
(s.e.)	(0.004)	(0.034)	(0.003)	(0.000)	(0.033)
Difference	-0.035	-0.057	-0.041	-0.035	-0.034
(s.e.)	(0.004)	(0.008)	(0.006)	(0.004)	(0.004)
<i>P</i> -value	0.0001	0.001	0.367	0.111	0.079
One Year					
Pre-correction average	0.064	0.075	0.058	0.064	0.061
(s.e.)	(0.013)	(0.018)	(0.005)	(0.013)	(0.013)
Post-correction average	-0.070	-0.107	-0.094	-0.072	-0.068
(s.e.)	(0.013)	(0.017)	(0.016)	(0.006)	(0.013)
Difference	-0.134	-0.182	-0.152	-0.136	-0.129
(s.e.)	(0.013)	(0.020)	(0.014)	(0.017)	(0.005)
<i>P</i> -value	0.000	0.000	0.000	0.071	0.000
Two Years					
Pre-correction average	0.092	0.086	0.056	0.092	0.087
(s.e.)	(0.021)	(0.009)	(0.008)	(0.004)	(0.012)
Post-correction average	-0.124	-0.193	-0.183	-0.127	-0.120
(s.e.)	(0.022)	(0.031)	(0.031)	(0.014)	(0.022)
Difference	-0.216	-0.279	-0.239	-0.218	-0.207
(s.e.)	(0.022)	(0.028)	(0.012)	(0.013)	(0.003)
<i>P</i> -value	0.000	0.031	0.000	0.000	0.000

Table 4
Average Change in Probability of House Price Correction Using the Two Components of the Long-Term Interest Rate and other Explanatory Variables during Pre- and Post-Correction Periods

Note: The table shows the average change in probability during a two-year window prior to the start of the house price correction ("pre-correction average") and during the two-year period following the start of the correction ("post-correction average"). Also shown is the average difference between the two periods along with the marginal significance level of a statistical test of the difference ("*P*-value"). The probabilities are the fitted values from the panel logit models shown in Table 2 that use the two components of the long-term interest rate as a measure of the monetary policy stance of the central banks. The logit models probabilities are calculated for three forecast horizons: house price corrections starting next quarter, house price corrections starting sometime in the next year and house price corrections starting sometime in the next two years. The standard errors shown in round brackets are robust to clustering at both the country level and over time (Thompson 2011).

	(1)	(2)	(3)	(4)	(5)
	Base case	Base case + Total (real) credit (all)	Base case + Total (real) credit (banks)	Base case + Total credit/GDP (all)	Base case + Total credit/GDP (banks)
One Quarter					
Pre-correction average	0.016	0.029	0.019	0.016	0.016
(s.e.)	(0.005)	(0.032)	(0.008)	(0.030)	(0.005)
Post-correction average	-0.021	-0.045	-0.032	-0.022	-0.021
(s.e.)	(0.004)	(0.012)	(0.000)	(0.000)	(0.005)
Difference	-0.038	-0.074	-0.052	-0.038	-0.037
(s.e.)	(0.004)	(0.011)	(0.016)	(0.005)	(0.005)
<i>P</i> -value	0.000	0.018	0.000	0.097	0.101
One Year					
Pre-correction average	0.061	0.093	0.065	0.062	0.060
(s.e.)	(0.018)	(0.006)	(0.016)	(0.016)	(0.006)
Post-correction average	-0.085	-0.145	-0.121	-0.086	-0.082
(s.e.)	(0.015)	(0.022)	(0.028)	(0.016)	(0.015)
Difference	-0.146	-0.238	-0.186	-0.147	-0.142
(s.e.)	(0.015)	(0.022)	(0.019)	(0.003)	(0.016)
<i>P</i> -value	0.000	0.000	0.000	0.009	0.033
Two Years					
Pre-correction average	0.092	0.108	0.070	0.096	0.093
(s.e.)	(0.036)	(0.041)	(0.052)	(0.036)	(0.035)
Post-correction average	-0.161	-0.267	-0.238	-0.170	-0.162
(s.e.)	(0.032)	(0.011)	(0.039)	(0.009)	(0.038)
Difference	-0.253	-0.375	-0.308	-0.266	-0.256
(s.e.)	(0.032)	(0.048)	(0.014)	(0.010)	(0.009)
<i>P</i> -value	0.000	0.000	0.000	0.045	0.000